2013-09-23

Design and Analysis of an Intelligent Decision Support System for Trading and its Application to Electricity Trading

Maurice, Sebastian Augustine

UNIVERSITY OF CALGARY

Design and Analysis of an Intelligent Decision Support System for Trading and its Application to Electricity Trading

by

Sebastian Augustine Maurice

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE

DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

CALGARY, ALBERTA

SEPTEMBER, 2013

Abstract

The financial trading market is a highly complex and dynamic system, which is the limiting factor preventing any model from accurately predicting its movements. Because of this limiting factor, trading in a market can be risky for individuals and institutions that could experience financial losses and this can impact the overall economy. It remains an on-going research challenge to find approaches to minimize the risk in trading.

The focus of this PhD research is on a multi-agent based simulation approach to provide decision support to traders to help minimize the risk from trading. We address four problems in the existing research on decision support systems for trading: 1) lack of a modeling framework, 2) lack of direction on modeling personas, 3) lack of direction on how to provide decision support to traders, and 4) lack of analysis on quality of forecasts.

The main contributions of the research is the design, analysis, development and validation of a new decision support paradigm for trading called T-Evolve*. We have also developed a new intelligent decision support technology called TRAMAS. The paradigm together with TRAMAS supports traders by allowing them to simulate different market models composed of agents with different personas and forecast beliefs. Exploring and analysing the simulation results provides guidance to traders on potential market outcomes; this is then used to develop a trading plan for tomorrow's market.

The core element of TRAMAS is the incorporation of actors with different personas and forecasts beliefs, instantiated by agents. The advantage of our approach is twofold. First, different personas of participants exist in every market, thus incorporating personas is a natural representation of the real market. Second, forecast beliefs are a natural belief of participants because forecasts about the future market play a critical role in how a market may develop tomorrow.

Two industrial-oriented case studies with empirical evidence support our approach. The validation of our approach by nine industry experts confirms, within the context of this research, that our approach has merit and can be useful in a real-world setting. TRAMAS also predicts with 77% accuracy the direction of future markets for six different days.

Acknowledgements

This PhD has been difficult and a hard road for my family and me mainly because I am a part-time PhD student trying to balance the demands of work, family and research. A few times the intensities and difficulties of maintaining a balance was almost too difficult to bear but with the support from family, friends, my work, and my supervisors, who believed in the ideas, I endured.

I cannot say I would recommend my road to others to follow – it was difficult and required total dedication and commitment that may sometimes be overwhelming. One has to be prepared to sacrifice the things they cherish, not for months, but years.

However, while the road is hard and demanding, there is nothing sweeter, other than the birth of our daughter, which can compare to having completed the arduous journey to a PhD; completing it is my Mount Everest. It is the ultimate accomplishment in academics and a valuable prize to attain.

I am greatly indebted to both Dr. Ruhe and Dr. Denzinger. When I first met Günther in 2003 I was contemplating a MSc. in Electrical and Computer Engineering and realized Günther was starting to build a lab in Decision Support. This area intrigued me and hence I completed my MSc. in Software Engineering in 2006. From that experience, I got to know him well. He has always been supportive of my research and always prepared to offer help and suggestions. I appreciate his rigor and always striving to instill in his students to be the best in the world in their research areas. After my MSc, I left for a year and during this time got the urge to pursue a PhD and approached Günther again in 2007. From then to now with a LOT in the middle I am here completing my PhD.

During the process of my PhD, I met Jörg. I cannot say enough good things about him. We had many conversations, some intense, in the areas of my research. His quick insights into the darkest corners of my research were enough of a light to continue in the area. His feedback and insights were invaluable to this research. I will also never forget his quick wit and laughter but mostly I will not forget his acute reasoning skills and his abilities to see issues or value before others.

My wife was a pillar of support in this long journey. The sentences I write here will not do justice to the tremendous love and support she continuously provides and for urging me to the finish line.

My mother and father must also be thanked for their continued support and encouragements and giving me life and dedication to higher learning.

Lastly, I would like to thank God for making me who I am and giving me certain talents that have allowed me to never quit what I start and remaining calm and focused even in the most difficult and trying moments in life.

I will also miss the experiences and interactions with Graduate Students in the lab but I will never be far. Thank you to all!

Sebastian Maurice
Calgary, Canada, 2013

Dedication

Mom and Dad

This thesis is dedicated to my mother Mary and father Francis, for instilling in me a commitment to hard work and dedication to academics and learning.

Ellen

Especially, I dedicate this thesis to my wife Ellen, for her continued support over the years, and for her patience in putting up with my pursuit of this degree.

Matea

Lastly, I dedicate this thesis to my daughter Matea; hope she will also value hard work and pursue great academic achievements.

Table of Contents

List of Tables

List of Figures

List of Symbols

The following is a list of symbols used in the dissertation and the sections they are first mentioned.

Variables	Description	Values	Section
α_{it}	Shape parameter that modifies the forecast for the *i*th seller. Replace *i* with *j* for the *j*th buyer.	*t*=1,...,24 If trader does not believe in the forecast: $-1 \leq \alpha_{it} \leq 1$ If trader does believe in the forecast: $\alpha_{it} = 0$	Section 1.7
ζ_t	A random variable to add noise to the probability of reward function of inexperienced and experience agents.	$0 < \zeta_t \leq 1$.	Section 1.7
β_{it}	This parameter is the price markup or discount. See the equation for estimated price below.	For aggressive (a) and non-aggressive (na) seller agents: $0 \leq \beta_{it}^{a} < \beta_{it}^{na} \leq 1$ For aggressive (a) and non-aggressive (na) buyer agents: $0 \leq \beta_{jt}^{na} < \beta_{jt}^{a} \leq 1$	Section 1.7
p_{it}	The estimated price for the *i*th seller for hour *t*. Replace *i* with *j* for buyer.	$p_{it} \geq 0$	Section 1.7
F_t	The actual forecast (i.e. Weather or Load)	If weather forecast, then it is temperatures in Fahrenheit If Load, then it is megawatts (MW) of electricity	Section 3.4.1
F'_{it}	The modified forecast for the ith seller.	$= F_t * (1 + \alpha_{it})$	Section 3.4.1
$p_{it}^{a(*)}$	The submitted price by an aggressive seller *i* for hour *t*. Replace *i* with *j* for buyer.	$= p_{it} + (p_{it} * \beta_{it}^{a})$	Section 3.4.1

$p_{it}^{na(*)}$	The submitted price by a non-aggressive seller *i* for hour *t*. Replace *i* with *j* for buyer.	$=p_{it} + (p_{it} * \beta_{it}^{na})$	Section 3.4.1
$q_{it}^{a(*)}$	The submitted volume by an aggressive seller *i* for hour *t*.	$= \frac{p_{it}^{a(*)}}{\vartheta_i^a} * \alpha_{it}^a$	Section 3.4.1
$q_{it}^{na(*)}$	The submitted volume by a non-aggressive seller *i* for hour *t*.	$= \frac{p_{it}^{na(*)}}{\vartheta_i^{na}} * \alpha_{it}^{na}$	Section 3.4.1
$q_{jt}^{a(*)}$	The submitted volume by an aggressive buyer *j* for hour *t*.	$= \begin{cases} q_{jt}^{a(*)} * (1+\beta_{jt}^a), & p_{jt-1}^{a(*)} > p_{jt}^{a(*)} \\ q_{jt}^{a(*)} * (1-\beta_{jt}^a), & p_{jt-1}^{a(*)} < p_{jt}^{a(*)} \end{cases}$	Section 3.4.1
$q_{jt}^{na(*)}$	The submitted volume by a non-aggressive buyer *j* for hour *t*.	$= \begin{cases} q_{jt}^{na(*)} * (1+\beta_{jt}^{na}), & p_{jt-1}^{na(*)} > p_{jt}^{na(*)} \\ q_{jt}^{na(*)} * (1-\beta_{jt}^{na}), & p_{jt-1}^{na(*)} < p_{jt}^{na(*)} \end{cases}$	Section 3.4.1
$\prod$	Agent reward	$\prod \in \mathbf{R}$	Section 3.4.1
ϑ_i	Slope of the supply curve for *i*th seller.	$\vartheta_i > 0$	Section 3.4.1
φ_j	Slope of the demand curve for *j*th buyer.	$\varphi_j < 0$	Section 3.4.1
Ψ	Intercept term in the weather forecast regression equation	In a two variable regression model this term contains the value where the regression line intersects the y-axis.	Section 3.4.1
Θ	The slope term which are in the weather and load forecast equations. This term will be different in the two equations.	The slope terms represents the slope of the regression line.	Section 3.4.1
$\rho_1 - \rho_6$	Indicates transition between information forms. The subscripts indicate the number of the transitions in case study #1.	$\rho_1$indicates from transition 1 to 2 $\rho_2$indicates from transition 2 to 3 $\rho_3$indicates from transition 3 to 4 $\rho_4$indicates from transition 4 to 5 $\rho_5$indicates from transition 5 to 6 $\rho_6$indicates from transition 6 to 7	Section 5.2.7

$\tau_1 - \tau_4$	Indicates transition between information forms. The subscripts indicate the number of the transitions in the trace data analysis in case study #2	$\tau_1$indicates from transition 1 to 2 $\tau_2$indicates from transition 2 to 3 $\tau_3$indicates from transition 3 to 4 $\tau_4$indicates from transition 4 to 5	Section 5.4.7

Glossary of Terms

Below are definitions of terminology used throughout the research proposal and the sections they are first mentioned:

Term	Section
• **Agent**: A computer system that is *situated* in some *environment*, and that is capable of *autonomous action* in this environment in order to meet its design objectives [Wooldridge and Jennings 1995].	1.1
• **Aggressive agent**: An agent is aggressive if the price it buys at is more aggressively priced than other buyers, and the price it sells at is more aggressively priced than other sellers. For example, an aggressive buyer may offer more money to buy an asset than other buyers. An aggressive agent who is a seller may sell an asset for less than other sellers. Aggressiveness is captured by the β variable defined in the symbols table.	3.3
• **Case study**: "Is an empirical method aimed at investigating contemporary phenomena in their context" [Runeson & Host 2008].	1.8
• **Decision Support System (DSS):** "…is the use of any plausible computerized or non-computerized means for improving sense making and/or decision making in a particular repetitive or non-repetitive business situation in a particular organization" [Alter 2004, p323].	1.5
• **Experienced agent**: An agent that has less or no noise in their decision-making. A noise variable, ζ, is added to an agent's probability of reward function, discussed below. The ζ variable is defined in the symbols table.	1.3
• **Expert System**: A system that simulates the behaviour of a human that has expert knowledge in a particular field. The expert system uses a knowledge base that contains accumulated experience of an expert and a set of rules that are applied to the knowledge base to solve each new situation that is presented to the expert system [Gottinger et al., 1992].	See IDSS

• **Financial Market**: A term used to define the existence of multiple entities, i.e. buyers and sellers, that engage in the buying and selling of listed commodities and stocks with a counterparty for the purpose of maximizing monetary profits. This market must have a moderator to manage the buying and selling of commodities or stocks [Frankfurter 2006].	1.1
• **Financial Market Trader (or just Trader):** An entity that buys from, or sells to, a counterparty any listed commodities or stocks, for the purpose of monetarily profiting from the trade.	1.1
• **Forecast Shape (or just Shape):** A modification of the original forecast based on the users' belief. For example, over a 24 hour period, power demand (i.e. load) has a "shape" meaning low power consumption in the morning, higher in the midday, and lower again in the late nights; since power cannot be stored, it must be supplied on demand.	1.10
• **Forecast belief**: Given a particular data forecast $\boldsymbol{F_t}$ for tomorrow, where *t* is time, a forecast belief about $\boldsymbol{F_t}$ is whether it is true, or not true. If not true, a user can shape the forecast. See the symbols table definition for $\boldsymbol{F_t}$.	1.1
• **Inexperienced agent**: An agent that has more noise in their decision making. A noise variable, ζ, is added to an agent's probability of reward function, discussed below. The ζ variable is defined in the symbols table.	1.3
• **Intelligent DSS (IDSS):** "is an interactive tool for decision making for well-structured (or well-structurable) decisions and planning situations that uses expert system techniques as well as specific decision models to make it a model-based system (integration of information systems and decision models for decision support)" [Gottinger et al., 1992, p.318].	1.5

• **Market**: A term used to define the existence of multiple entities, i.e. buyers and sellers that engage in the buying and selling of goods, services or information for the purposes of maximizing value or utility; this value or utility is of a type that is acceptable to the parties that participate in the exchange [Frankfurter 2006].	1.1
• **Market Component:** Anything that is perceived to have an observable influence on a market.	1.1
• **Market Model:** Any instantiation or model of a market composed of combinations of market components that are chosen based on the users' beliefs about the future market.	1.1
• **Non-aggressive agent:** An agent is non-aggressive if the price it buys at is less aggressively priced than other buyers, and the price it sells at is less aggressively priced than other sellers. For example, a non-aggressive buyer may offer less money to buy an asset than other buyers. A non-aggressive agent who is a seller may sell an asset for more than other sellers. Aggressiveness is captured by the β variable defined in the symbols table.	3.3
• **Persona:** A social role or a character played by an actor that will be instantiated by agents in TRAMAS	1.1
• **Potential Market Outcome (PMO):** For a given market model, a PMO is a result of the iterations in the simulation generated by agents' actions. It is a snapshot in time of what a future market may look like.	1.1
• **Power Price Similarity (PPS)**: We use a variant of the measure proposed in [Sueyoshi 2010b]: PPS = $\frac{\lvert \textbf{\textit{real market price}} - \textbf{\textit{estimated market price}} \rvert}{\textbf{\textit{average real market price}}}$ Where the estimated market prices are the simulated prices and the real market prices are the PJM RTO real-time prices.	2.6
• **Simulation**: Process of designing a model of a real system conducting experiments with this model with the purpose of either	1.1

	understanding the behaviour of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system [Shannon 1977].	
•	**Simulation Round:** Signifies the bidding process, which starts with every agent submitting buy or sell price and quantity combinations in the market, and ends with a market clearing agent clearing all bids to form the market price curve. Agents use the probability of rewards to adjust their price and quantity combinations in the hopes of profiting from the trade in future rounds.	2.8
•	**Trace Data:** Are data representing the influence on market components from agents' actions.	3.2

Acronyms

Following are a list of acronyms used throughout the thesis.

Acronym	Meaning
BW1_Y	Bad weather, scenario 1, all agents believe in the forecast
BW2_N	Bad weather, scenario 2, all agents do not believe in the forecast
BW3_Y	Bad weather, scenario 3, all agents believe in the forecast
BW4_Y	Bad weather, scenario 4, all agents believe in the forecast
BW5_N	Bad weather, scenario 5, all agents do not believe in the forecast
Expagg	Experienced and Aggressive Agent
Expnonagg	Experienced and Non-aggressive Agent
GW_Y	Good weather, all agents believe in the forecast
GW_N	Good weather, all agents do not believe in the forecast
Inexpagg	Inexperienced and Aggressive Agent
Inexpnonagg	Inexperienced and Non-aggressive Agent
PMO	Potential Market Outcome
PPS	Power Price Similarity
Simid	Simulation ID
TRAMAS	TRAding Multi-Agent Simulator
WD1_Y	Weekday, scenario 1, all agents believe in the forecast
WD2_N	Weekday, scenario 2, all agents do not believe in the forecast
WD3_Y	Weekday, scenario 3, all agents believe in the forecast
WD4_N	Weekday, scenario 4, all agents do not believe in the forecast
WE1_Y	Weekend, scenario 1, all agents believe in the forecast
WE2_N	Weekend, scenario 2, all agents do not believe in the forecast

CHAPTER 1: INTRODUCTION

1.1 Motivation

A corporation's success is closely linked to its ability (or inability) to make good decisions [DeGregorio 1999]. Knowing what may happen tomorrow is critical for success, however getting access to good information from which good decisions can be made to accurately know what may happen tomorrow is the most challenging part for a business [Raberto et al., 2001]. A motivating factor for this research is the need to minimize trading risk. Chaotic markets of the last few years fuelled by complex and nonlinear feedbacks that caused the boom and bust of the dot-coms and housing bubbles, was mainly due to large institutions taking on extreme risk in pursuit of higher profits [Buchanan et al., 2009]. Complex mathematical models did little to help avert the crisis. An agent-based approach is at the forefront to effectively analyse a constantly changing market. This is because it makes minimal assumptions about human behavior, or inherent market stability [Buchanan et al., 2009]. The idea is to build a virtual market with interacting agents that act much like real people in the real market.

Market complexity is heightened by dependencies between changing individuals' beliefs, institutions, and other dynamic factors that no one model can accurately capture. Trading decisions are extremely strategic and tactical, mainly because human beings are involved. Adding to the complexity is that trading among humans mainly happens anonymously in markets. This raises tactical questions, such as should I buy or sell to this individual? How much should I buy or sell? When should I buy or sell? Etc. To help provide answers to these questions our research develops a systematic approach to show how the combination market data' forecast beliefs and individual personas impact how the market may evolve.

An ad hoc approach to establishing trading strategies and plans would only increase trading risk and heighten the chances of losses, and this is counterintuitive to what the objective of trading should be: to make profits. While a more systematic approach does not guarantee more profits it does provide a means to minimize risk by modeling and exploring simulated results for insights before participating in the real-market.

As a consequence to the efficient market hypothesis (EFM [Fama 1970]) past performance of an asset cannot help in predicting future performance because markets are constantly changing, driven by the rationality or irrationality of traders. Even more challenging, but critical for success, is adjusting information based on the changing market conditions resulting from different variables and re-forecasting or re-planning what may happen tomorrow. Building artificial markets has been one approach to better understand market dynamics by modeling important market components. The work done at the Santa Fe Institute [Palmer et al., 1994; LeBaron et al., 1999] was pioneering in the area of computer simulated artificial markets. Since then, several authors have developed artificial markets with heterogeneous agents with learning capabilities. We add to this area by building a general multi-agent based simulation technology with machine learning capabilities that incorporates human personas and forecast beliefs in actors that are instantiated by agents, we call our technology TRAMAS (TRAding Multi-Agent Simulator). We highlight the effectiveness of our approach by two extensive case studies with empirical evidence using actual market data. The first case study presents online survey results from nine industry experts who confirm that our approach has merit and could be useful in a real-world setting. The second case study performs analysis of trace data from simulations and shows that TRAMAS correctly predicts the direction of future markets 77% of the time for six different days.

TRAMAS differs from other technologies such as PowerWeb [Zimmerman et al., 1999], Agentbuilder [Acronymics, 2004], SEPIA [Samad et al., 1996], MASCEM [Praca et al., 2003] EMCAS [North et al., 2002], MAIS [Sueyoshi et al., 2008] in two main ways: a) we define actors with different personas that are instantiated by agents; b) these agents have different (or they can have the same) forecast beliefs about the future market data, relative to other agents. By modeling a) and b), along with other market components, and then simulating the market model and exploring the results allows users to gain insights into how the market may evolve tomorrow.

1.2 Trading and Software Engineering

Software Engineering is still challenged by its inability to answer the crucial questions of “How”? “How good”? “When”? “Why”? And “Where”? [Fenton 2001; Ruhe 2004]. From a trading perspective, How to trade? How good is the trade? When to trade? Why to trade? And, where to trade? These are all critical questions that impact the success of a trader. These questions with related topics are addressed in Empirical Software Engineering (ESE), which is a discipline "concerned with the scientific measurement, both quantitative and qualitative, of Software Engineering process and product" [Jeffrey & Scott 2002]. Activities in Software Engineering research typically fall into one of the following three areas [Jeffrey & Scott 2002]:

1) To invent new phenomena
2) To understand existing phenomena
3) To facilitate inspirational education

Our research falls into categories 2) and 3). In 2), we try to understand how changes in personas and forecast beliefs impact the market outcomes such as prices to help us identify opportunities and threats in this market. By using the industry needs and vision as the driving force, our understanding of the impacts could help in theory building based on empirical evidence. In 3) our approach educates traders on market fundamentals related to the above questions. By educating traders in the market, it is hoped that they can avoid mistakes and make careful or risk-focused trading decisions. By showing how different market models can impact trading profits and giving users the flexibility to construct other models, simulating these models and exploring the results is how our approach helps traders learn the market.

1.3 Trading and Software Engineering Decision Support

As part of this research we have developed a new decision support paradigm called T-Evolve*, which is based on an evolutionary problem-solving process [Ruhe 2004; Wang & Ruhe, 2007; Ruhe 2010]. It combines both human and computational intelligence to explore alternative PMOs constructed from different market models, to help identify potential opportunities and threats in the market using profits and probability of rewards as selection criteria to differentiate between different PMOs. Users can identify which trades have the highest probability of reward, which trading strategies are better than others (i.e. make more profits), whether inexperienced agents make more profits than experienced agents and how differences in forecast beliefs and personas affect prices in tomorrow's market.

Trading decisions are complicated by changing market conditions, changing market data, changing stakeholders and actors, changing regulations, changing socio-economic, political factors and many more product or asset specific factors. The approaches taken to help making trading decisions are diverse. However, if we look carefully at the research on trading, and ask ourselves ‘what is the research trying to achieve?’ the answer that one draws is not clear when it comes to providing decision support for traders. Specifically, there is no consensus in the research on a systematic approach to providing decision support. There is no consensus on a modeling approach or an approach that can consistently offer good insights in an evolving market. While no one system can accomplish all things, what we have proposed is a general modeling approach to analysing a market.

1.4 State-of-the-Art in Agent-Based Modeling

The emergence of “agent-oriented software engineering” (AOSE) [Bernon et al., 2005] and “agent-based modeling and simulation” (ABMS) [Macal et al., 2007] are being recognized as emerging areas that will have a significant impact on science and society in the following years [Cossentino et al., 2010; Farmer et al., 2009; Buchanan et al., 2009]. [Cossentino et al., 2010] further emphasize that the methodological and technological trends in the convergence and integration of AOSE and ABMS should be widely explored to provide future research directions.

The advantages of agent-based modeling have given rise to many applications that help researchers develop a MAS. The notable tools are GAIA [Wooldridge et al., 2000], Tropos [Mouratidis et al., 2007], Prometheus [Brans et al., 1986], INGENIAS [Pavon et al., 2003], PASSI [Burrafato et al., 2002], ADELFE [Bernon et al., 2006], PASSIM [Cossentino et al., 2008], and for simulation tools for the analysis of complex systems modeled as multi-agent systems one could consider Repast [ROAD, 2005], Swarm [http://www.swarm.org/], Netlogo [http://ccl.northwestern.edu/netlogo/], and Mason [http://cs.gmu.edu/~eclab/projects/mason/]. The applications of agent-based simulation are almost limitless, for this research we find little in the way of standard ways to design agents with different personas and forecast beliefs about the future market and how markets can be analysed in a systematic way. Next we define the research problems.

1.5 Research Problems

The main problem area for this research is how to provide effective decision support to traders to help them make more risk-focused trading decisions. Taking up this challenge is important for several reasons: 1) taking into account all of the financial market variables, modeling them, and simulating their actions, is a daunting task, if not impossible [Huang et al., 2010]. These authors also state that forecasting the depth and length of market movements is hard if not impossible to forecast but that identifying fundamental factors is possible. 2) Accurate prediction of financial market prices will be difficult to achieve in the long-run [Haefke et al., 2000]. Even employing powerful mathematical models to predict stock market prices have produced less than successful results in practice [Haefke et al., 2000; Sevastianov et al., 2009].

We find four problems in the existing research on trading and decision support.

1.5.1 Problem 1: Lack of a Modeling Framework

The importance of a modeling framework for trading is important not only for a structured analysis of markets that can be repeated in a systematic way, but also to increase transparency in the decision making process [Lim et al., 2010]. Yet in the state-of-the-art there is no clear modeling framework using MAS with an IDSS to show how users can construct market models using different market components to learn market fundamentals. A modeling framework also facilitates learning that to some extent, can lead to better long-term results as users continue to understand the reasons behind market movements and what gives rise to volatility in the market. Perhaps a reason for the lack of a modeling framework is that there is yet no consensus in the literature as to the best way to analyze a financial market. Without a proper framework for market analysis, validation of the results and learning become difficult to measure and even more important they become difficult to replicate and reuse. However, addressing this problem creates some challenges.

- **Challenge 1:** The difficulties in building a generic framework are tempered by the fact that a market has many influencing factors and so the challenge is how to accommodate for all these factors such that an instantiation of the general modeling framework to a particular market results in an effective and realistic abstraction of a real market. Since there is no consensus, we have many ways to approach how we build this framework. In this case, it becomes important that one has industry knowledge because in many cases what is practiced in industry is not always apparent in the published literature as this could give away competitive advantage. It can also be added that the trading business and market is quite protective in releasing or communicating trading methods or strategies to external communities.

- **Challenge 2:** Choosing personas such that they are representative of the real market but still maintain a simple interface for the users can also be challenging. Traders' behaviours, emotions, aggressiveness, as discussed above, all contribute to the dynamics of a market in different ways [Mayall 2009]. Traders, who may behave rationally one day, may behave in an irrational way the next; rational behavior in trading does not necessarily lead to more profits or less risk [Franci et al., 2001]. In addition, modeling the experience and inexperience of traders, which is a trait of different types of traders can also affect the market outcomes. An experienced trader may be able to make more sound decisions leading to more calculated actions and potentially higher profits, whereas an inexperienced trader may make more mistakes leading to potentially less profits; but in trading this may not always be true. How we model experience within a multi-agent simulation model is the challenging aspect.

1.5.2 Problem 2: Lack of Direction on Modeling Personas

There is a lack of research that examines how personas affect market outcomes, and how this can be modeled? Specifically, markets are composed of individuals of different personas; these different personas influence individuals' actions, which lead to certain market outcomes. This problem creates the following challenge.

- **Challenge 3:** The state-of-the-art is in agreement that different behaviours should be modeled. However, there is no consensus on the types of behaviours that should be modeled. A common type of behaviours is someone who is a risk taker or someone who is a risk avoider [Sueyoshi et al., 2005; Sevastianov et al., 2009]. However, there are also studies that show that cloudy days affect trader's behaviours relative to sunny days [Chang et al., 2008]. So, how does one model a trader type? There are no hard and fast rules and researchers have experimented with and developed modeling practices that are specific to the area or situation they are studying and not a generalized concept that can be used in other areas in a systematic way.

1.5.3 Problem 3: Lack of Direction on Providing Decision Support to Traders

There is a lack of research on how decision support should be provided to traders. Specifically, there is no consensus on how traders should be trained or educated on a market. This problem creates the following challenge.

- **Challenge 4:** Decision support provided to traders should align with the information needs of the trader. However, determining the information needs of traders varies between markets. Thus, it becomes important to have an understanding of not only the market but also the traders in this market and what their information expectations are.

1.5.4 Problem 4: Lack of Analysis on Quality of Forecasts

There is a lack of direction on modeling and analysis of how different forecast beliefs held by different types of agents affects trading decisions. This problem creates the following challenge.

- **Challenge 5:** The state-of-the-art does not explicitly help suggest effective modeling approaches that answer the question: "What if the forecast used to make market predictions, by different types of market participants, is not correct?" What we mean by "not correct" is it has wide variations when compared to the actual data it was forecasting. In certain markets, the degree of variation will vary. For example, if the forecast is off by 10% then this may not be material in one market, but in another market it may be quite material. Therefore, market knowledge becomes critical to understand the difference between a good forecast and a bad forecast for different markets.

1.5.5 Further Problems and Challenges

In addition to the problems and challenges described above, there exist more challenges with multi-agent based simulation. One key challenge is validation of the results. This area has garnered very little attention in the literature [Weidlich et al., 2008]. One reason why this is more difficult in the trading research is due to the volatility of prices. For example, prices generated from a simulation would need to be compared against the real market prices in similar conditions but due to volatility in the real market getting similar price magnitudes and trends may be difficult to achieve because the financial market is constantly evolving. However, it may be possible to choose a less volatile period in the market, such as a weekend, that could facilitate a reasonable comparison between simulated and observed prices. Lack of validation can affect the credibility of the simulation results and influence the usability of the simulation technology [Macal et al., 2007]. Next, we discuss the research questions.

1.6 Formal Problem Definitions

In order to formally state the problem that we address in this thesis, the following fundamental factors are defined. For a formal definition of the trade planning problem we make the following assumptions:

1. A set *M* of market components $c_1, c_2, \ldots, c_n$ and agents $Ag_1, Ag_2, \ldots, Ag_m$ with forecast beliefs $\alpha_1, \alpha_2, \ldots, \alpha_m$, aggressiveness $\beta_1, \beta_2, \ldots, \beta_m$ and experience $\zeta_1, \zeta_2, \ldots, \zeta_m$ are to be integrated into a market model *Z,* to eventually produce new PMOs $(pmo_1, pmo_2, \ldots, pmo_k)$ from which a trade plan can be derived.
2. Let $K = \{k_1, k_2, \ldots, k_K\}$ be the set of trade plans in which the trades are assigned.
3. Each trade plan shows the assignment of trades and positions to each hour for the next day. Let TR= {tr(1), …tr(N)} be a set of candidate trades. Then the decision variable d(n) (n=1,…, N) helps to define the trading strategy that assigns the trades to a plan based on the answers to the following questions:
    a. Is the trade part of the next K day's trades (where K=1, which means we are only considering trades for tomorrow's market)?
    b. If yes:
        i. D1: What is the position of the trade (i.e. buy or sell)?
        ii. D2: What is the hour of the trade?
        iii. D3: What is the price being bid or offered?
        iv. D4: What is the quantity being traded?
4. So each individual trade plan shows the assignment of trades for the next day's trades. It is characterized by a vector d = (d(1), …, d(N)) defined by:
    a. d(n) = K if trade tr(n) is traded tomorrow (n=1,…,N)
    b. d(n) = K+1 if trade tr(n) is not traded tomorrow (n=1,…,N)

5. A PMO is a simulated output of the market model Z, and is made up of prices $p_1, \dots, p_{24}$, quantity $q_1, \dots, q_{24}$, calculated profits $\pi_1, \dots, \pi_{24}$ and probability of rewards $pr_1, \dots, pr_{24}$.
6. Each trader is interested in maximizing profits from a trade plan. Nevertheless, it may be the case that the best trade plan generates losses rather than profits.
7. Each trade plan $k \in K$ has an associated total value, which is a function of the prices, quantities, profits and probability of rewards for each k.
8. Bounded rationality: each agent's decision making is limited by the information it has access to.
9. In our research we define four personas as follows:
    a. Aggressive and experienced (expagg),
    b. Aggressive and inexperienced (inexpagg),
    c. Non-aggressive and experienced (expnonagg)
    d. Non-aggressive and inexperienced (inexpnonagg)

    The above is not a complete list, rather indicative of natural personas for traders.

We can now state the trade planning problem as follows: *"Given a set of market components M and agents Ag with associated sets of forecast beliefs and personas, find an assignment of trades to a sequence of trade plans from PMOs* $pmo_1, pmo_2, \dots, pmo_k$ *such that the implementation of M and agents in the market model represents the user's beliefs of how tomorrows market may evolve, and the total value of the trade plans are maximized."*

The planning problem is illustrated in Figure 1-1 below. The set of market components consist of forecast data, agents with different persona types and forecast beliefs. The creation of market models from the set of market components is an evolving process; the choice of market components is based on the user's beliefs on how the market may evolve tomorrow as well as the insights provided from the exploration of different PMOs. The decision making problem is to choose a final trade plan from a set of different PMOs such that the final trade plan gives the highest potential of profits for the trader. The selection of trades from the PMOs is based on the probability of rewards of each trade. The higher the probability, the higher the chances of earning a profit from that trade in the real market. The selection of the final trade plan requires decision support to help answer D1-D4. Specifically, trade plans (see Appendix D show hour, position, price, and probability of reward. Using the probability of reward and profits as selection criteria for the trades is an important way to prioritize which final trades to make tomorrow. While there is no guarantee that the final trade plan will result in profits, the final trades should be chosen such that the chances of making profits are the highest. The usefulness of our approach is supported by nine industry experts in case study #1. The accuracy of our results is compared against actual data in case study #2.

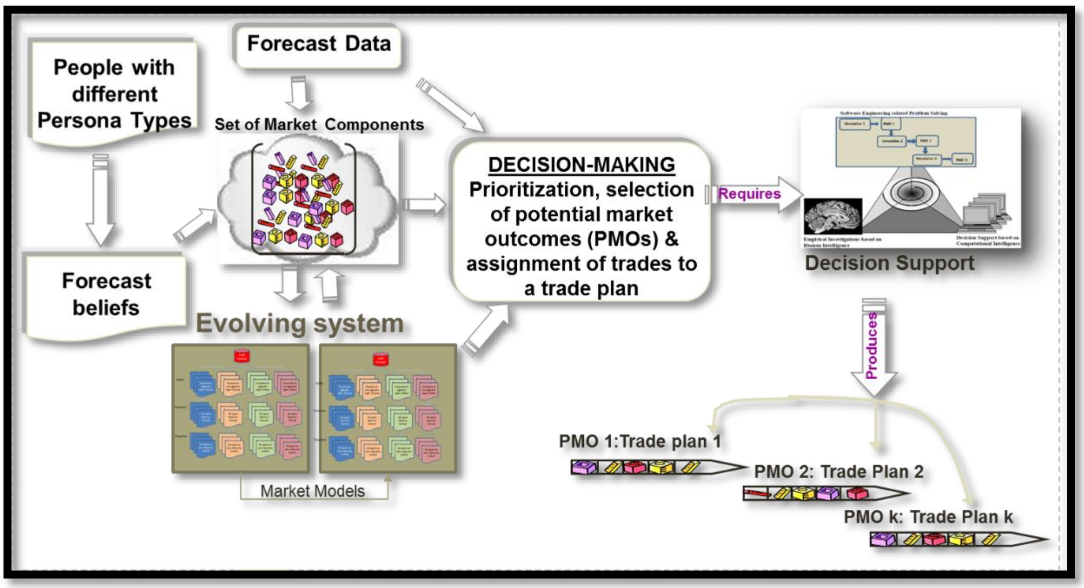


Figure 1-1: Planning Problem

1.7 Research Questions

From the above problems, we have identified six research questions that will be answered in this thesis:

R1) What is the overall evaluation of TRAMAS by industry experts?

R2) How does this evaluation change by an expert's business role?

R3) How do the experts describe their experience with TRAMAS?

R4) Does the differences in forecast' beliefs and personas cause different bidding strategies?

R5) Does the differences in forecast' beliefs and personas cause an increase in profits under one condition but not in others?

R6) Does more experience cause agents to earn more profits than less experience?

Two case studies are conducted to answer the above questions. Case study 1 answers R1-R3 by analyzing the results from an online survey of nine industry experts. Case study 2 answers R4-R6 by providing empirical evidence from the application of the T-Evolve* paradigm using actual market data.

1.7.1 Addressing the Research Challenges

This research would not have been possible or at least very difficult, if not for the TRAMAS system that we built here. To address challenges 1 and 2, we propose an approach that incorporates personas in actors' instantiated by agents with forecast beliefs that specifically targets the human aspect of trading. While trading is getting more automated with speed being one of the components of success in some markets, for us, speed is not as important, as we are planning for tomorrow's market. By choosing the market components as we have, allows us to effectively capture some of the influencing factors in the real-market. Due to the authors industrial knowledge in the trading domain helps to identify certain approaches, such as how agents participate in the market, how the market clears, and how learning helps to determine trading strategies. Whether these challenges are effectively addressed is the reason for the evaluation research questions (R1-R3): to determine whether TRAMAS is a useful approach for industry use or not. The online survey results from experts (Director, Manager, and Sr. Analysts) in energy trading suggest that it is useful for industrial use.

To address challenge 3 we use personas such as the level of experience and aggressiveness that vary between agents as chosen by the user. These personas affect trading behaviours in agents and allow us to model different types of behaviours [Benos 1998]. He argues that aggressive trading is similar to being overconfident and results in the trader trying to overinvest such to limit others from entering the market. We use three parameters to model these behaviours: α to capture forecast beliefs, β to capture the level of aggressiveness, and ζ to capture experience levels. Modification of these parameters will be critical in the modeling and simulation of market models.

To address challenge 4, we develop a new decision support paradigm called T-Evolve*. We show how an evolutionary problem solving approach to finding the best trade plan can be an effective decision support approach for traders. We also show how SQL queries can be used to extract insights from agents' trace data. The types of insights we can extract (but not limited to) are: best trades, average profits from strategies, actual and simulated profits for buyers and sellers, graphs of α and β, profits and probability of rewards for buyers and sellers, and similarity analysis of how close prices are to average and actual prices. While it is a future enhancement to automate the extraction of information, currently this was a manual process by the author.

To address challenge 5, we use the α parameter to capture the modified forecast, as chosen by the user, for the simulation. The modified forecast is when a user does not believe in tomorrow's forecast and chooses to modify it with the belief that this is how the actual market will evolve. For example, load and weather forecasts are used in our simulations. These forecasts are for tomorrow's market and they may represent how the real-market evolves or they may not. If the user believes that the forecast is not a representation of the real market, then α captures the adjustments he makes to the original forecast in percentage values for each hour of the day.

Research questions R4-R6 help us to gain insights in to our approach to address the challenges. How personas and forecast beliefs influence behaviours and how these behaviours materialize into profits by agent types and whether they produce signs of emergent behaviours are all critical outcomes from our approach. From these insights they assist the user to determine the trade plan for tomorrow's real-market, if he chooses to participate. Our research contributions are discussed next.

1.8 Justification for Taking a Rule-Based Approach

As mentioned above many authors have used various techniques to analyse a financial market in an effort to profit from trading. The approaches and techniques develop mathematical forms that, hopefully, capture some dynamic in the market being analysed. One of the most popular of these models is the Black-Scholes (BS) formula [Black & Scholes, 1973] which is used to price options[1] as follows.

---

[1] In financial terminology an option gives the buyer (owner) a right but not the obligation to purchase or sell an asset at a specified strike price a a specified date.

$$V(S,K,T,r,\sigma) = SN\left(\frac{\ln(\frac{S}{K})+\left(r+\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}\right) - Ke^{-rT}N\left(\frac{\ln\left(\frac{S}{K}\right)+\left(r-\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}\right) \quad (1\text{-}1)$$

where S is the underlying stock, K the strike price, T the maturity date, r the risk-free interest rate, *N* is the cumulative standard normal distribution function, and σ the volatility. While it is beyond the scope of this thesis to go into any great depths in explaining the theoretical rationale that gave rise to this formulation, what is critical about this formula is the role volatility plays in pricing options. Indeed a critical assumption in the above formula is that there is no way to make a riskless profit [ibid.] i.e. there is no arbitrage possibility. In very volatile markets, like electricity, the underlying distribution of the data generating process could be a highly irregular if not a chaotic process which could make the pricing of options by this formula highly uncertain or even mis-price certain options under these conditions.

Researchers [Abidin et al., 2012] argue that mathematical models such as Hidden Markov Model (HMM), high-order fuzzy time-series model, moving average autoregressive exogenous (ARX), rough sets (RS), Markov Fourier Grey Model (MFGM), Clustering-Genetic Fuzzy System (CGFS) are not suitable for short-term investments. Other techniques such as Artificial Neural Networks (ANN) may not be suitable for predicting prices because they involve the use of fuzzy systems and the involvement of experts [ibid.]. For these reasons Geometric Brownian Motion (GBM) models are needed for short-term investments due to a higher level of volatility in short-term markets [ibid.].

The question to ask is what happens if the market changes? Does the same model, as discussed above, hold all the time for all conditions? Obviously not, but the risk is that many traders still believe in some way that the same mathematical model holds in many different situations or scenarios, when this may not be true. It is the abuse of these models by humans by applying them in situations where they should not be applied in cases of high volatility is one of the reasons we had the financial crisis in 2008 [Farmer et al., 2009]. [Crotty 2009] states that commonly used models (such as VaR (Value at Risk) models) in the financial industry assume that prices are generated by a normal distribution, but there are times when prices are so far from the mean that they fall in the “fat tails” i.e. extreme areas of the normal distribution.

Game theory is potentially another area that can be useful in modeling markets. While game theory was not used in their work [Kidney & Denzinger, 2006] show how agents can use stereotypes to model other agents. [Wang, 2008] shows how a game theoretic approach could be useful when the environment of a decision maker is interactive with ones decisions or the environment changes or is influenced by the actions of the decision maker which follow from the strategies or rules he uses; this decision making can be classified in the category of games. The modeling of other agents offers many opportunities to allow an agent to modify its strategies for greater payoff in a zero-sum game such as trading. However, in the current implementation of TRAMAS a game theoretic approach or stereotypes was not used simply because the intent was to start with a well-established approach as presented by [Sueyoshi et al., 2005] and evolve the approach over time. Also while it is possible to incorporate stereotypes and game theory in TRAMAS, the T-Evolve* process in many ways allows users the flexibility to model other agents by creating market models in a way that aligns with their beliefs of how a market may evolve tomorrow. The evolutionary process of decision-making as developed in the thesis lends itself to a type of decision-making that is on the surface supportive of the Definition 2 in [Wang, 2008, p. 206]:

> *Definition 2. A game is a decision process under competition where opponent players or opponent groups of players compete for the maximum gain or toward a success state in the same environment according to the same predetermined rules and constraints of the game.*

In TRAMAS, agents submit their prices into the market in each simulation round along with other agents in the market. Agents are autonomous and do not know who else is in the market. The agent's decision process is to calculate a price using their beliefs about the forecast data and a price markup or markdown variable called β which ranges based on the persona type of the agent. If this variable generates a likelihood of reward that meets an acceptable level of reward, which is a parameter in TRAMAS, then the agent submits that price, otherwise it does not. Agents compete to make a profit from their trade in each round. All agents have a set of rules that are specific to their persona type and role as a buyer or seller. If one agent is an aggressive buyer, it does not know what a non-aggressive seller will do, or what an another aggressive buyer will do because each rule is not the same since the selection of rules is determined by coefficients in the profit equations (discussed below) which captures the learnings of the values of β used in previous rounds that were successful in helping the agent win a trade. However, one agent could guess what another agent's β variable may be and factor that into its variable. For example

$$\beta_i^{na} = f\left(\beta_j^{na}\right) + \text{error} \tag{1-2}$$

The formulation in Eq. (1-2) says that a non-aggressive seller's β_i^{na} is a function of the buyers β_j^{na} who is in the same environment plus some error term. This error term could capture the level of confidence a non-aggressive agent has in the formulation of Eq. (1-2). We do not intend to go into great depths on game theory, but it is an area where TRAMAS can evolve to as part of the future research.

Using an evolutionary decision making process, with a rule based and mathematical model approach embedded in an agent-based simulation technology can be effective in this environment. Clearly there is no perfect mathematical, or market, model to predict with certainty future prices. And no one model can capture all of the dynamics in a market. For this reason a rule-based approach is used together with mathematical models to predict prices and bid prices into the market. The approach follows [Sueyoshi et al., 2005] and why it makes sense for this thesis can be classified in five areas:

1) Rules can better capture the qualitative aspects in the market [Carvalho et al., 1999]. As we do in this thesis, aggressiveness and forecast beliefs can be factored into the rules more easily, or in a less complicated manner, than in a mathematical model.
2) Rules are flexible and can more easily reflect changes in the market by adding more rules or changing existing rules [Helbing et al., 2012].
3) Rules can specify more generally the interactions and behaviours of agents through if – then kinds of rules [ibid.].
4) Rules can make it easier to consider variations due to random influences [ibid.]. As we do here, past trading successes can help agents learn and more systematically help to choose the best rule for the next round.

5) Rules can help in increasing the transparency in trading which removes the "black-box" view of some mathematical models. In this way, trading losses can be traced back to the rules used in making those losing trades.

1.9 Research Contributions

In this dissertation, we propose a decision support approach for helping traders minimize the risk from trading by making more risk-focused trading decisions. This first objective leads to building market models that align with the users' expectations on how tomorrow's market may evolve. The second objective is to explore and analyse the different PMOs by adapting the T-Evolve* paradigm to identify potential opportunities and threats that may exist in tomorrow's market. The end goal of the analysis is to find a trading plan comprised of the best trades for tomorrow's market.

This research presents a number of contributions to the field of empirical software engineering. These contributions are as follows:

1) **Decision Support Paradigm for Trading:** We have developed a new decision support paradigm for trading called T-Evolve* that shows how the evolutionary approach to problem-solving is directly applicable to the financial trading domain. To our knowledge, this is the first time this approach has been applied to this domain. Specifically, our contribution to methodology adapts the Evolve* paradigm to create a new paradigm specific to the trading domain. This thesis is the first application of the T-Evolve* paradigm. The contribution to methodology is how we apply T-Evolve* to help provide intelligent decision support to trader in the following ways:
    - Creation of market models as chosen by the users' beliefs about tomorrow's market using a multi-agent based model that incorporates persona types and forecast beliefs by agents.
    - Simulation of the market models to produce a potential market outcome (PMO) that is amenable to data mining for insights.
    - Exploration of the PMO to help provide insights on tomorrow's market and help build a trade plan.

- Building new market models that uses the insights attained from the results of the exploration of previous PMOs.
- Ability to consolidate the information in different PMOs to build a final trade plan for tomorrow's market using the profits and probability of rewards generated by each plan to select and prioritize the best plans.
- We incorporate learning by creating profit equations and converting these equations into logistic regression models to determine the probability of reward from a trading strategy. The results of this estimation helps agents to choose the best bidding strategy.

2) **Prototype Tool:** We have developed a new trading simulator that incorporates human personas and forecast beliefs into agents for trading. TRAMAS is a flexible and customizable technology that can potentially be applied to any market. This contributes to the body knowledge in intelligent decision support system and agent based technology by:
   - Presenting a user-friendly interface that is used to build and simulate market models
   - Showing a method of analysis using SQL queries to analyse the trace data from agent interactions for insights
   - Developing and showing how an integration between a MAS and an IDSS is used to provide decision support to traders

3) **Incorporating Personas and Forecast Beliefs:** We have developed a novel approach that allows users to modify forecasts used by agents in forming price bids for tomorrow's market. By having agents in the market with different forecast beliefs and personas a user is able to observe and predict how tomorrow's market may evolve under a similar market model. This, in part, is a realistic way of modeling a market because a forecast is not perfect and many times wrong. Simulating the effects of wrong forecasts allows users to see the market from different perspectives so they can make better decisions about how and what to trade and when. This contributes to the method of analysis of how differences in personas and forecast beliefs can produce different market results, such as changes in prices, which helps the user formulate a final trade plan for tomorrow.

4) **Bidding Strategies:** We also develop bidding strategies that build on the work of [Sueyoshi et al., 2005] by taking into consideration different forecast beliefs (and personas) and show how strategies differ between agents who believe in the forecast and those who do not believe in the forecast. These bidding strategies can be helpful for users (experienced or inexperienced) to decide how, what and when to trade in a market. This is even more important for inexperienced traders who can have the ability to learn market fundamentals more quickly. Specifically, we contribute to formulae. We extend the bidding strategy formulae in [Sueyoshi et al., 2005] as follows:
   - We extend the strategies from 9 to 36 by incorporating persona types and forecast beliefs for buyers and seller.
   - As a result, additional insights are provided by showing that persona types and forecast beliefs do have impact on the profits or losses by agents. We show this by simulating market models with specific persona types and forecast beliefs.
   - The thirty-six If-then rules we create is a minimum set of rules for the four agent types. Additional personas will add to this list.
5) **Information Access:** We offer a way to easily access information to allow users to make quicker trading decisions by adapting the T-Evolve* paradigm. Access to good information can be a challenge especially when timing is an important factor in trading success. By writing tailored SQL queries a user can easily explore the data from the simulations to get a better understanding of tomorrow's market.
6) **Evaluation of Forecast Beliefs on Rewards:** We also show the impacts of different forecast belief on agents' rewards or profits. It is useful to show the user if their modification of the forecast actually results in more or less rewards. If less rewards, it may be that the modified forecast should take another shape. If the actual forecast results in more rewards, then this may show that the actual forecast is reasonably good. Incorporating forecast beliefs into the agent's decision making allows users to simulate many different type of beliefs as they see fit.
7) **Modeling Experience:** We show how experience and inexperience is modeled in the probability of the reward function of agents. Experience plays an important role in

trading mainly due to the speed of changes in a market. However, what may be more important is the impact inexperienced traders can have in the market. Inexperienced traders typically trade with more noise in their decisions than experienced traders. Therefore, knowing how rewards differ between experienced and inexperienced agents could offer further insights into determining whether tomorrow's market will be more or less volatile.

8) **Case Study Results Adding to Theory Building:** Empirical evidence from two extensive case studies answer research questions R1-R6. For case study 1, nine (9) industry experts evaluated the TRAMAS system providing five findings. One of the main findings showed experts found TRAMAS to be 'close to comprehensive coverage' of financial trading. For case study 2, the analysis of the simulation results show that differences in forecast beliefs and personas do lead to different bidding strategies with impacts on trading profits.

[Stol and Fitzgerald 2013] describe theory in software engineering as defining the relation between constructs and how they interact with one another. Theories have limited scope indicated by their boundaries that make them valid only under certain conditions, which is related to the concept of generalizability or external validity. A theory can have different states with different set of laws that apply only to that state. Thus constructs, relations, boundaries and states are all elements of a theory that must be given consideration when building or adding to theory [ibid.]. In TRAMAS the construct of a market model made up of components (i.e. different agents' types, different forecast beliefs, more buyers than sellers, etc.) is simulated to produce a PMO. From the T-Evolve* paradigm, new market models will be generated by the user based on different market components. From the simulation of each model under different states such as: hot weather conditions, weekends, weekdays, good weather, and major storm event, we can show how these market models relate under these scenarios; this will be analysed in case study #2. From the findings, within the scope of this research, we can provide insights that can lead us towards generalizability of trading behaviours by human participants in the real market.

1.10 Organization of the Dissertation

Figure 1-2 below shows the organization of the dissertation:

Chapter 1 – Introduction

This chapter introduces in a general sense why this research is relevant. It presents a discussion on the state-of-the-art. This chapter also presents the motivation, problems and challenges that are addressed by our research, and discusses how it is connected to Software Engineering Decision Support and Empirical Software Engineering. At the end, it presents an overview of the chapters in the thesis.

Chapter 2 – Literature Review

This chapter first describes the process of conducting a systematic literature review. It describes the search strategy, search terms, classification scheme and describes the relevant research in the areas of focus for this thesis and who has done what, when and how it relates to this research as well as concepts that enable the research.

Chapter 3 – Trading Simulation Methodology

This chapter presents the trading simulation methodology with a focus on the T-Evolve* process. Specifically, it describes in detail the evolutionary problem-solving process steps. It discusses the market models, and shows how the market models used in the analysis are constructed. The TRAMAS simulation process is also discussed in detail. The chapter ends with a summary.

Chapter 4 – TRAMAS: Architecture

This chapter presents a discussion of the TRAMAS architecture and design, as well as providing formal definitions. A discussion of the TRAMAS simulation model, decision support, and how it is instantiated to the electricity market is done. TRAMAS application is also discussed within the context of the overall solution.

Chapter 5 – Experimental Evaluation and Validation

This chapter conducts two case studies. The first case study analyzes survey results from nine (9) experts in the energy trading industry and answers the research questions R1-R3. The second case study addresses the three research questions, R4-R6, and performs validation of the simulated results against real-data. The chapter includes an evaluation and implication of the results, threats to validity and discusses inferences from the results.

Chapter 6 – Conclusion and Future Research

This chapter summarizes all of the main points in the thesis. It summarizes the linkages between the concepts, the application and the results generated. It also discusses how the challenges are addressed. It evaluates TRAMAS from a decision support perspective. It discusses the effort versus benefit of using TRAMAS. It also provides details on the limitations of TRAMAS. It concludes the thesis with outlook on future research directions.

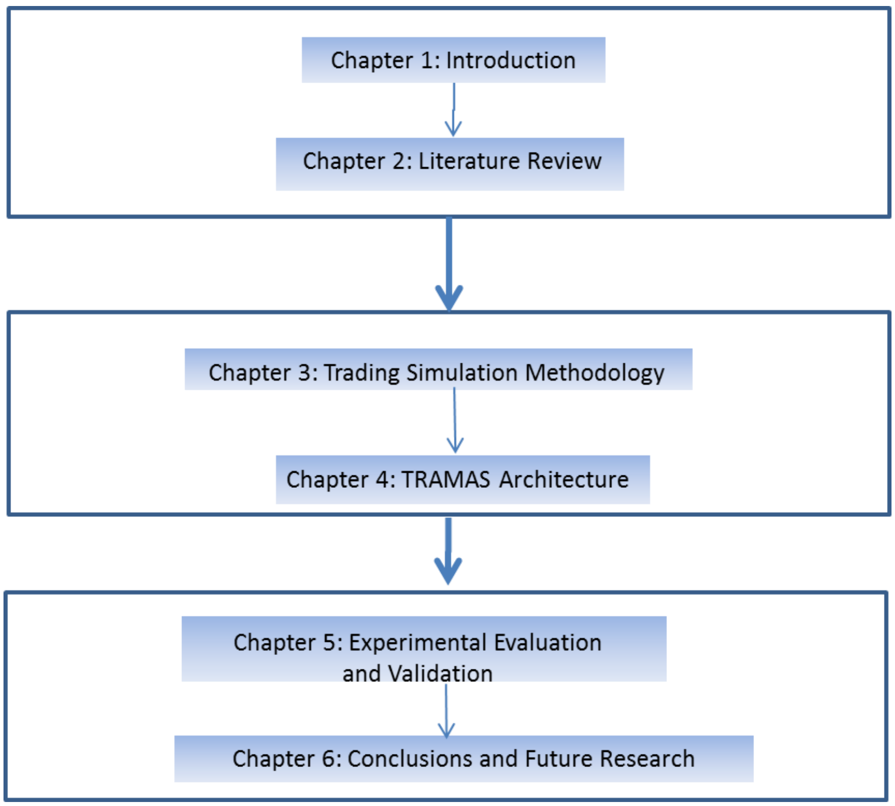


Figure 1-2: Thesis structure

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Based on the above information the problems and challenges in this thesis come from the areas of decision support, MAS, and trading. While there is vast amount of research in each of these areas alone, there is interrelation between some or all of these areas. From an application perspective, the growth of research in these areas is not constrained to academics but extends to industry. For this reason, this research has practical relevance beyond academics.

2.2 Review Approach

Following the approach proposed in [Kitchenham, 2004; Kitchenham, 2009; Petersen et al., 2008] a review is conducted to investigate more concrete questions in the area of intelligent decision support systems for trading using a multi-agent simulation approach.

For this research, a search strategy was executed that involved using commonly used research databases that are the major sources of software engineering related studies. The six databases are shown in Table 2-1.

Table 2-1: Research Databases

Database
ACM Digital Library
IEEE Xplore
Science Direct
Springer Link
Scopus
Engineering Village (Compendex & Inspec)

The search terms used to find the studies relevant to this research are shown in Table 2-2. Note that the search terms a, b, and c are not used separately but in conjunction with other terms. A search log was used to keep track of all selected or rejected studies to ensure a transparent and repeatable process.

Table 2-2: Search Terms

No.	Search Terms
A	*"Intelligent Decision Support System for trading"*
B	*"multiagent simulation for trading"*
C	*"trading simulation"*
1	{a} AND {simulation or multiagent or trading} AND electricity
2	{a,c} and {MAS or multiagent} AND electricity
3	{trading, simulation, multiagent, multi-agent, MAS, Decision Support}
4	3 and {Electricity}
5	{a,b,c} and {Electricity}
6	trading AND decision support AND simulation
7	5 OR 6
8	6 AND {MAS or multiagent or multi-agent} AND electricity

The process of selecting the relevant studies is as follows. The total search resulted in 4,784 papers. Using a basic inclusion and exclusion criteria looked at the title of the studies resulting in 435 papers. By further removing duplicates and reading the title, abstract and keywords resulted in 197 unique papers.

The second phase applied a more detailed inclusion and exclusion criteria shown in Table 2-3. Applying the detailed criteria by reading the title, keywords and abstracts resulted in 91 papers. These papers were then classified based on the work activity carried out in the research.

Table 2-3: Detailed Inclusion and Exclusion Criteria

No.	Detailed Inclusion Criteria
1	The paper describes the design and implementation of an intelligent decision support system for trading as applied to electricity market with analysis of the output data.
2	The papers uses a multiagent simulation approach to model a market with in a trading context
3	The paper describes the validation of the multiagent simulation model
4	The paper provides an overview of multiagent simulation models
5	The paper can be a mapping study, systematic review, literature survey, case study, technical report, an experiment, position paper, industrial experience report, or action research related to intelligent decision support and multiagent simulation modeling within a trading context, where applicable.
	Detailed Exclusion Criteria
7	The articles that are not peer reviewed and do not provide a full text of the core context.
8	The papers that relate to the development or coding phase of an intelligent decision system for trading will be excluded.

9	When there are several papers describing the same system or tool, the most recent paper will be selected and the rest excluded, where appropriate.

The complete process is shown in Figure 2-1 below:

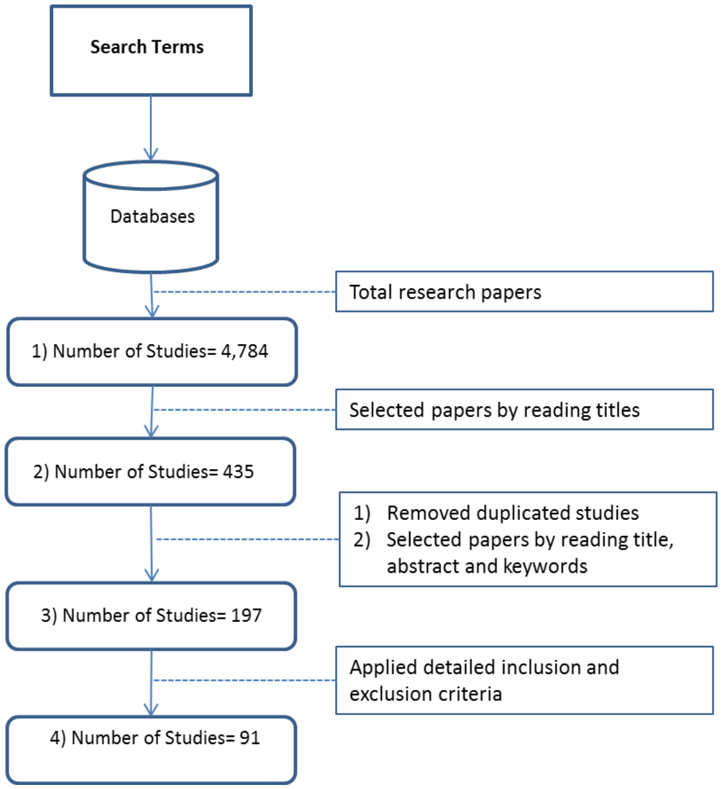


Figure 2-1: Paper Review Process

The studies chosen for this research ranged extensively in terms of approach and context; our approach also tried to achieve a level of granularity based on the inclusion and exclusion criteria and the search terms used. While some papers put more weight on modeling and design and lesser weight on validation and analysis, other studies did the reverse. So while there is no standard way to approach a simulation study or any standard way to validate one [Wang, et al., 1997; Sevastianov, et al., 2009; Baqueiro, et al., 2009] mainly due to the different beliefs of each researcher and the context of the study, four aspects for classification were identified: 1) model and design characteristics, 2) simulation type characteristics, 3) analysis performed on the output data, 4) validation performed or discussed on the simulation model. Figure 2-2 shows the classification of papers per publication year. The size of the bubbles indicates the numbers of papers in a particular classification or category. It should be clear from the chart that the validation of simulation models is critically lacking in the literature.

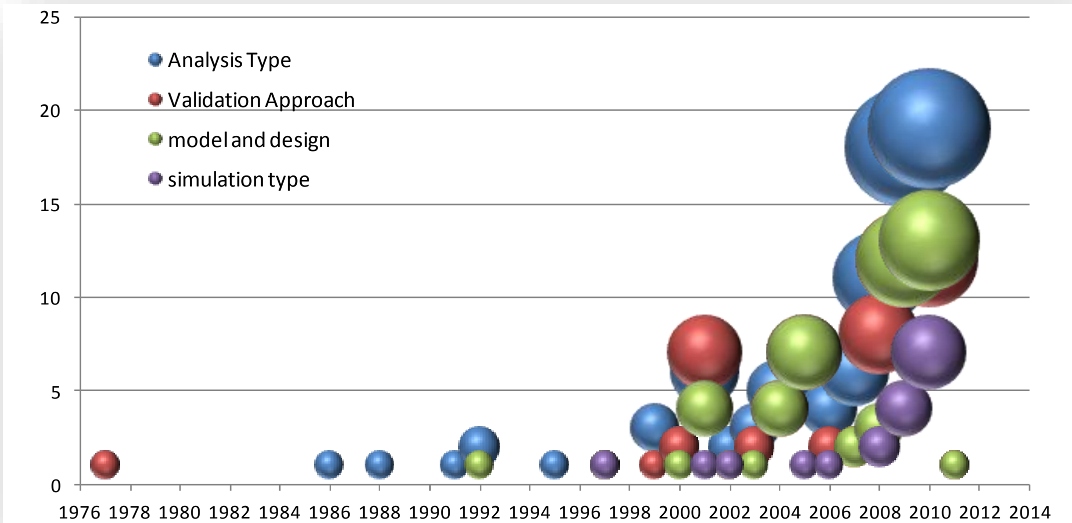


Figure 2-2: Classification by Publication Year

As seen in Table 2-4, out of the 91 papers identified, with some papers overlapping categories, only 8% discussed or actually validated their simulation model with the real environment that was being simulated; while 42% discussed model and design, 28% described the simulation type and approach, and 22% discussed and described the type of analysis of the simulation data.

Table 2-4: Breakdown of Papers per Classification Scheme

Model and Design	Simulation Type	Analysis Type	Validation Approach
42%	28%	22%	8%

From the above list of papers we have some key findings discussed in the sections below. These findings are also additional motivation for this research.

2.2.1 Lack of Validation by Industry

Out of the papers chosen, the vast majority of the papers were academic and a minority was industry focused. Below Figure 2-3 shows the research methodologies that are validated in academics or industry for the 91 selected papers; the data are shown in Table 2-5.

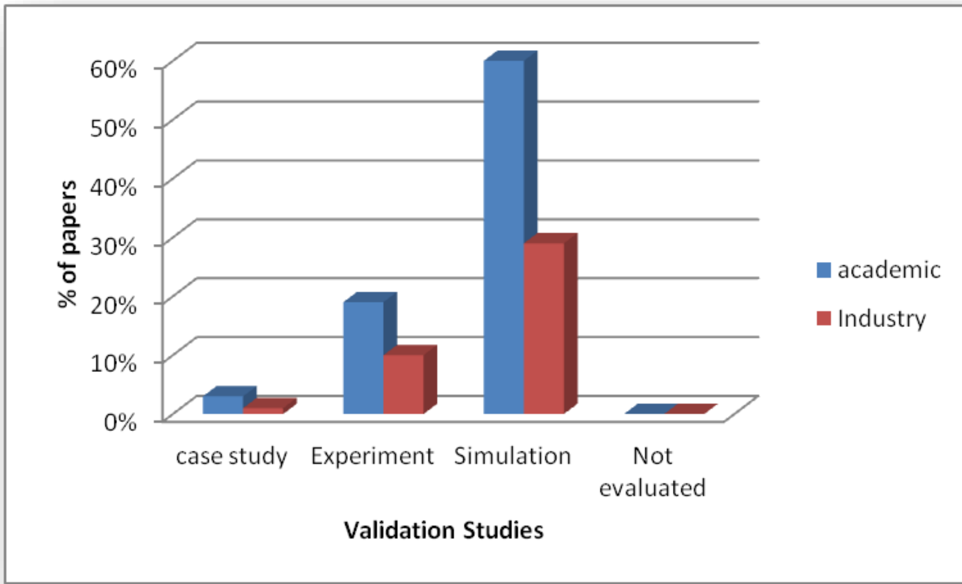


Figure 2-3: Research Methodologies by Validation Types

Simulation is the most common and validation is commonly conducted in an academic setting at 60%, followed by experiments and then case studies. Industry validation is lacking but it is no doubt an important part of validation. There is also no clear method to validate modeling constructs or results with industry. A survey approach is by far the most popular but this approach has limitation mainly due to lack of response rates and the objectivity of the response due to bias. This thesis uses industry experts to validate the modeling constructs of TRAMAS and finds general acceptance by industry experts on these constructs. The importance of industry involvement adds credibility to the modeling approach and the potential usefulness of TRAMAS in addressing industry problems.

2.2.2 Lack of Case Study Research

From Table 2-5 the simulation approach is by far the most used within an academic setting this would make sense as access to industry in many cases is difficult. The importance of case study research is in part due to the combination of both quantitative and qualitative strategies that can help in the systematic improvement of understanding and baselining the problem by looking at the past results, then evaluating the problem by using case studies, and improving upon the understanding with study outcomes [Wohlin et al., 2003]. In this thesis our case study approach helps combines both quantitative and qualitative strategies to determine the outcomes against a defined baselined model to shed light on the research problems.

Table 2-5: Validation of Studies

	Academic	Industry
Case study	3%	1%
Experiment	19%	10%
Simulation	60%	29%
Not evaluated	0%	0%

The papers are discussed below in sections. The next section discusses the main papers in multi-agent based simulation.

2.2.3 Lack of Systematic Approach to Trading Analysis

Another issue is the lack of a systematic approach to trading or market analysis that is easily repeatable. An easily repeatable process allows experiments to be replicated to determine if the actual outcomes are scientifically credible or simply a symptom of some ad hoc or random process. One key objective of this thesis is to have a systematic approach to trading analysis and allow for a process that could be easily repeated. This modeling approach allows for easy repeatability and experimentation, with outcomes that can be measured against some baseline model.

2.3 Multi-Agent Simulation (MAS)

MAS approach is a sensible and effective way to model trading markets [Buchanan et al., 2009]. These technologies capture market dynamics in unique ways that does not use special mathematical models as the only source of estimation, or make special assumptions on the distribution characteristics of market data. Formal definitions of agents and MAS are proposed by [Kidney and Denzinger, 2006] and capture the main components that can be used to describe a general agent that can be instantiated to many problem domains. The advantage of an agent-based approach is exactly because one is not forced to make distributional assumptions of the data. Researchers incorporate personas: risk avoider and risk-taker [Sueyoshi et al., 2005; Sueyoshi et al., 2007; Sueyoshi et al., 2008; Praca et al., 2003; North et al., 2002] in their MAS. Authors usually focus on the risk levels of agents when analysing a market but we show that other factors such as experience level of agents and their aggressiveness could provide important information on how a market may evolve. From Sueyoshi's papers, starting in 2005, the machine learning approach developed in these papers is relevant to this thesis. This approach allows for functionality in each agent in an analytical way to determine the probability of reward from a potential trade before actually making the trade. In this thesis we modify this approach by taking into account the personas of each agent and their forecast beliefs, which they do not account for. This is a more realistic way, we think, to model trading agents because personas and beliefs play a critical role in the decisions of actual traders. Bidding strategies, as developed by Sueyoshi, are modified and enhanced to account for agents' forecast beliefs and personas.

2.4 Design and Analysis of Multi-Agent Based Simulation Models

Other papers focus on the design and analysis of a multi-agent based model [Frankfurter 2006; Denzinger & Hamdan 2004; Kozhan et al., 2004; Farmer et al., 2009; Buchanan 2009]. [Baqueiro et al., 2009] show how data mining and agent-based systems (ABS) can be integrated. The data mining of agents' data, as part of the analysis component of TRAMAS will be an important aspect of this thesis in the case studies below. Finding patterns in the data will help to identify buy and sell opportunities in the market for tomorrow. Our method differs in both the type of data used in the analysis and the visualization of patterns in the data that can help to provide decision support to traders. [Maes, et al., 1999] provide an overview of different areas of application of buying and selling agent technologies. However, they state that more work on agent technologies is needed. [Maenhoudt, et al., 2010] present an overview on the benefits and criticism of agent-based models and show how this tool can be employed to gain better insights in to complex market designs, policies and principles with respect to the more traditional tools. They show how agent based tools are well aligned to electricity markets. [Nikolaidou et al., 2009] describe a process used in the prediction of bidding strategies in trading agents. Actually, several authors have analysed bidding behaviors in electricity markets [Kian, et al., 2005; Bunn, et al., 2001; Chandarasupsang, et al., 2004; Qian et al., 2006; Walter, et al., 2008; Wen, et al., 2001]; all try to find optimal bidding strategies using a multi-agent simulation approach, and show how bidding behaviors differ between buyers and sellers as well as how strategies change based on different locations. By extending the approach in Sueyoshi, we show that agents' personas and forecast beliefs can be quite useful in choosing the best trading strategies and plan. The results are validated with real market prices.

2.5 Intelligent Decision Support Systems for Trading

Implementation of decision support technologies for trading should enable traders to manage the risks from trading [Arnott et al., 2008; Alter 2004; Gottinger et al., 1992]. [Chen-Ching, 2001] shows the types of research areas of interest in the electricity market domain where decision support technologies are used to help decision makers in both the operational and financial aspects of their operations. [Trigo et al, 2009] present an overview of intelligent decision support systems. These include artificial neural networks, evolutionary computing, fuzzy systems, case based reasoning, as well as multi-agent systems. Application examples show how intelligent and hybrid intelligent techniques can be utilized to tackle decision-making problems.

[Sueyoshi et al., 2008] develop a power trading simulation tool by allowing users to model and simulate a power market. Their decision support system allows users to test trading strategies in a competitive power market. Their simulator consists of many software agents that interact with each other and the power market (i.e. the environment) by observing the price fluctuations of the wholesale electricity market [ibid]. The generator is the seller of electricity and the wholesaler is the buyer. The strategies used by buyers and sellers incorporate machine learning and probability of reward algorithm to help buyers and sellers decide how to bid into the market. The MAIS model however does not incorporate explicit personas and forecast beliefs to simulate different market outcomes. The process of trading and bidding strategies presented by these authors is one of the few examples in the literature that uses the risk profiles of agents to establish price bids for buyers and sellers.

There are several concepts in MAIS that relate to TRAMAS. First, the knowledgebase concept is used in TRAMAS to facilitate the process of developing bidding strategies. The adaptive learning algorithm concept is also used in TRAMAS. However, TRAMAS adds personas to help agents formulate bidding strategies. Specifically, by adding personas such as the aggressiveness of agents and their experience levels, strategies can be separated into aggressive or non-aggressive for buyer and seller agents given their experience levels. This adds a further level of detail and more accurately represents the real market. Second, the concepts of supply and demand effectively segment the groups of buyer and seller agents so that buy and sell strategies can be applied separately to each group. Third, market data concept is used in TRAMAS for forecast data information that is used by the agents to form price predictions. Included here is the data query concept that is used in TRAMAS in the analysis stage. The querying concept is critical to provide business intelligence that help to answer D1-D4. In addition to lacking personas, the concept of forecast beliefs is not considered in their model.

[Denzinger & Ruhe 2004] suggest that uncertainty and incompleteness of information can be approached by generating alternative solutions and by exploiting human intelligence as an integral part of the solution generation process. This paradigm aligns well with trading and is directly applicable to the process of generating PMOs. [Ruhe 2010] builds upon the evolutionary problem-solving framework to show how the three phases of modeling, exploring and consolidating choose the most appropriate plan. Using these concepts, T-Evolve* shows how these phases are used to iteratively develop market models, explore the resulting PMOs from the simulation and consolidate PMOs based on some criteria. This process helps users to decide the best trades to use in the real market. Specifically, our approach shows how the best trading plan can be developed using the T-Evolve* paradigm.

The objective of [Teive et al., 2010] simulation and decision support system is to allow energy traders to execute what-if analysis that involve simulation of short-term energy markets. As they further state, with the use of the IDSS the trader agents can foresee opportunities as well as possible threats in the energy market enabling them to choose a contracts' portfolio that are more aligned to their risk profile. While the PMO concept in TRAMAS is different from [Teive et al., 2010], it does follow a similar direction. Specifically, the concept of a market model in TRAMAS is an effective way for users to simulate different market models to foresee opportunities and threats in the market that may develop. Using charts and reports can be an effective way for users to better understand the future market and determine if it aligns to their risk profile. In particular, the probability of reward will be used to determine whether a trade is likely to generate a reward (i.e. profit) for the agent. This concept is related to the adaptive learning algorithm discussed in [Sueyoshi et al., 2008].

2.6 Agent Trading Strategies and Classification

Consider trading strategies as a set made up of positions (buy, sell, or hold), prices, volumes, time, and product(s), then each trader will need to decide what position to take, what product to buy, when to buy it, how much volume to buy and at what price to buy at. There are many types of trading strategies in financial markets. [Bekiros, 2010] identify the common elements of their fuzzy actor-critic reinforcement learning system for trading in Table 2-6:

Table 2-6: Elements of Reinforcement from Trading

Environment	Historical Time Series Accessment by Analyst
State	Eight states corresponding to fuzzy inference rules to characterize the financial input variable based on the expected return and condition volatility
Policy	Output of the fuzzy inference system leading to a buy or sell trading decision
Action	The selected optimal parameter values by the agent representing the response to the environment
Reward	Prediction accuracy measured by the forecasting mean squared error

In TRAMAS, agents are able to learn from past simulation rounds by using the success rate of past bidding behaviour by estimating their profit equations (discussed in Chapter 3). Using the coefficients from these equations agents can determine the likelihood of rewards for the current simulation round. So moving from one simulation round to another are ***states*** that should allow agents to make trades that are reinforced by learning. There is no concept of ***policy*** that leads to a buy or sell in TRAMAS because this is a setting chosen by the user when he is creating the market model to simulate. Specifically, agents are designated as buyers or sellers before starting the simulation. ***Action*** concept in TRAMAS means that agent's calculate the strategy variables (α, β) then submit the price, and quantity, for each hour to the market. The action is predicated on the fact that the choice of (α, β) generates a positive reward. ***Reward*** is the settlement of the agents' trades at the end of each simulation round. The trades settle against the average historical real-time prices for each hour.

[Fahlenbrach et al., 2010] identify optional strategies that are commonly used in the industry as shown in Table 2-7.

Table 2-7: Option Trading Strategies

Strategy	Description
Put/call spread	Buy put (call), sell any put (call) at lower higher strike, same expiry
Put/call volatility trade	Buy put (call), buy (sell) underlying to give zero net delta
Straddle	Buy call, buy put at same price
Strangle	Buy put, buy call at higher strike price
Guts	Buy call, buy put at higher strike price
Calendar spread	Sell near month call (put) buy far month call (put)
Diagonal calendar spread	Sell near month call (put), buy any far month call (put) at a different strike
Ratio spread	Sell call (put), buy two calls (puts) at higher price
Butterfly	Buy call (put) at K_1, sell two calls (puts) at K_2, buy call at K_3 $K_1 < K_2 < K_3$ and $K_2 - K_1 = K_3 - K_2$
Condor (put)	Buy call (put) at K_1, sell call (put) at K_2 and K_3, buy call (put) at K_4 $K_1 < K_2 < K_3 < K_4$ and $K_2 - K_1 = K_3 - K_2 = K_4 - K_3$
Iron butterfly	Buy a straddle, sell a strangle
Iron condor	Buy a strangle, sell another strangle with more extreme strikes
Combo	Sell call, buy put at lower strike
Synthetic underlying	Buy a call, sell a put at the same strike
Reversal	Buy call, sell put at the same strike, sell underlying
Conversion	Sell call, buy put, buy underlying
Box trade	Buy call, sell put at same strike, sell call, buy put at higher strike same expiry
Jelly roll	Sell call, buy put at same strike in near month, buy call, sell put at same strike in far month
Ladder	Buy call (sell put), sell call (sell put) at higher strike, sell call (buy put) at equally higher
Strip	Buy between three and eight calls (put), strikes and expiry can be different
Straddle calendar spread	Sell Straddle in near month, buy Straddle in far month at same strike

The only strategy that is used in TRAMAS is a strip strategy, where agents who are buyers or sellers buy or sell a strip of trades. For example, if an agent buys each of the 24 hours, then the strip is 24 trades long. Note that the rest of the strategies are similar to arbitrage strategies, where traders can offset losses from one trade to hopefully profit from another trade. Arbitrage is currently not possible in TRAMAS, however this could be part of future research to extend the strategies to those in Table 2-7 to allow agents to arbitrage. What can be useful is to see how persona types influence the choice of trading strategies and how forecast beliefs affect returns?

[Chiam et al., 2009] develop a multi-objective optimization of technical trading strategies which lends to the development of trading rules that yield high returns at low risk. Technical indicators (TI) give traders signal to buy and sell where TI is defined as [ibid]:

$$TI : \{P_t, \dots, P_{t-n+1} \rightarrow [-1,1]\} \quad (2\text{-}1)$$

where $TI(P_t, \dots, P_{t-n+1}) = -1$ and $TI(P_t, \dots, P_{t-n+1}) = 1$ is a sell and buy signal, respectively. They define traders decision (D) by the rules:

$$D : \{TI_1, \dots, TI_m\} \rightarrow \begin{cases} Strong\ Buy, & if\ T_{buy-high} < D \leq 1 \\ Weak\ Buy, & if\ T_{buy-low} < D \leq T_{buy-high} \\ Hold, & if\ T_{sell-low} < D \leq T_{buy-low} \\ Weak\ Sell, & if\ T_{sell-high} < D \leq T_{sell-low} \\ Strong\ Sell, & if\ -1 \leq D \leq T_{sell-high} \end{cases} \quad (2\text{-}2)$$

where $-1 < T_{sell-high} < T_{sell-low} < 0 < \ T_{sell-low} < T_{sell-high} < 1$ are the four thresholds that dictate the trader's decisions with respect to the trading signal from the various TI. In TRAMAS we do not consider technical indicators in the agents bidding strategies. However, Eqs. (2-1) and (2-2) show how rules can be modeled to indicate what position agents should take. This is another area where TRAMAS can be extended to see how agents choose technical indicators with persona types and forecast beliefs that give them the best possibilities of making a profit.

[Szakmary et al., 2010] show how trend-following trading strategies yield positive mean results in 22 out of the 28 markets they studied. The trading rules they define earn significant returns across most sub-periods of their data set. [Izumi et al., 2009] show that automated trading strategies in their artificial market provide better information than conventional evaluation using backtesting. They also show that the impact of strategies may not only depend on the structure of the rules but the way the rules are combined with other strategies. However, while their results are interesting, their agents do not have any mechanism to estimate a price level from fundamental information such as performance of a company and economic conditions. Their agents also do not have any adaptive learning capabilities. However, they do consider this as for future research.

The trading strategies above and the different approaches offer promising new areas for TRAMAS. With the addition of persona types and forecast beliefs, within a multi-agent based simulation model, which none of the authors consider, could offer further insight on how these strategies can be chosen by agents and how effective the strategies may be in the real market.

2.7 Application and Evaluation of Multi-Agent Based Simulation Models

Several papers discuss the application of multi-agent based systems. [Davidsson et al., 2007] perform an evaluation of the research on ABS and discuss the lack in the literature on implementation and validation of the simulation model and results. They suggest a checklist for reporting on ABS. [Hongtao et al., 2010] use an agent-based modeling approach to construct an artificial stock market, where a limit order book was employed as a price formation mechanism. They also look at several psychological effects that describe agent behaviours. While the psychology of agents can drive certain behaviours it is not clear how these can be modeled in agents. Personas are one way to model agent' psychology and TRAMAS uses the differences in personas to determine how the price bidding behaviours of agents can help provide insights into how tomorrows market may evolve. The uniqueness in our approach is the addition of adding forecast beliefs into the agents decision making function. Forecast beliefs allow users to model the potential deviation of the market data forecast from what actually will happen. These deviations could impact how actual prices will deviate from estimated prices in the market, which will affect trading strategies and profits. [Pěchouček, et al., 2008] describes the deployment of MAS in an industrial setting. They discuss that not all agent concepts and technologies have been deployed in industry and there continues to remain challenges.

Table 2-8 below shows a comparison of how different models address the core components of agent based trading. The column on estimation indicates whether the model uses statistical estimation to make predictions, the transmission column indicates if the model provides decision making capabilities for decision support, analysis indicates if the model has an analysis component and the intelligence column indicates if there are any intelligence built into the agent decision making function. The last three shaded columns are specific to the additional functionality added in TRAMAS. The MAIS [Sueyoshi et al., 2008] model is perhaps the closest model to TRAMAS.

Table 2-8: Existing Technologies

Technologies	Estimation	Decision Making	Analysis	Intelligence	Incorporates Forecast Beliefs	Incorporates Market Beliefs	Incorporates Agent Personas
PowerWeb [Zimmerman et al., 1999]	No	Yes	Yes	No	No	No	No
Agentbuilder [Acronymics, 2004]	No	Yes	No	No	No	No	No
SEPIA [Samad et al., 1996]	No	No	Yes	Yes	No	No	No
MASCEM [Praca et al., 2003]	No	No	Yes	Yes	No	No	No
EMCAS [North et al., 2002]	No	Yes	Yes	Yes	No	No	No
MAIS [Sueyoshi et al., 2008]	Yes	Yes	Yes	Yes	No	Yes	No

2.8 Validation of Agent-Based Simulation Models

[Marks 2007; Naylor & Finger, 1967] discuss output and structural validation. The validation of the simulated output is compared to actual or observed data. The similarity between the estimated and observed prices in terms of the price magnitudes, descriptive statistics, and trends offer important information on how well the simulation represents the real-world. [Dey 1997; Robson 2002; Runeson & Höst 2009] show how case studies should be structured by clearly defining the objective, the case, theory, research questions and methods used. Case studies are an important part of the presentation of the validation results along with analysis to answer the research questions. The output validation concept will be used in the empirical validation chapter below. The approach is to use real or observed market data from the market TRAMAS is analyzing, and compare the similarity (using the power price similarity (PPS)) in the price magnitudes and trends with the TRAMAS simulated (estimated) data. The expectation is that the price and trends between the observed and estimated data are similar in percentage terms. The PPS metric is compared to other related studies.

[Sargent 1998] presents a simplified validation process. He defines the following: The problem entity is the system that is real or proposed, the conceptual model is the mathematical, verbal or logical representation of the system proposed, and the computerized model is the implementation of the conceptual model. Through an *analysis and modeling phase* the conceptual model is developed, along with the computerized model through a *computer programming and implementation phase*, and inferences about the problem entity are obtained by conducting computer experiments on the computerized model in the *experimentation phase*. He also states several model validity techniques such as face validity, which involves asking people knowledgeable about the system whether the model and/or its behavior are reasonable. Using this technique, one can determine if the logic in the conceptual model is correct and if a model's input-output relationships are reasonable [Sargent 1998]. He also suggests event validity, which compares the events of occurrences of the simulation model to those of the real system. Comparison to other models is also recommended.

Historical data validation is done by comparing the results of the simulation with historical data to see if the simulation behaves as the system does. Lastly, extreme condition tests, which shows that in cases where the model is given extreme values, that it produces plausible results. Concepts that are directly applicable to TRAMAS are the face validity of the results from TRAMAS by experts in the field. The event validity concept is employed in this research by seeing if the trends of the simulated prices follow the forecast data in a way similar to how actual prices follow the same forecast. The similarity in the trends is another indication that the simulation results are a reasonable depiction of what happens in reality.

2.9 Machine Learning

An adaptive sigmoid decision rule model in an electricity market trading simulator is an effective way to capture the learning dynamics from trading [Vriend 2003; Sueyoshi et al., 2005; Sueyoshi et al., 2008; Sueyoshi et al., 2010a; Sueyoshi et al., 2010b; Sueyoshi et al., 2010c]. Their approach shows how traders accumulate their knowledge and how they use their experiences for power trading. The learning process incorporated in the simulator is considered a computational approach in which a trader tries to maximize a total amount of reward obtained from power trading [Sueyoshi et al., 2005].

In many studies [Sueyoshi et al., 2005; Sueyoshi et al., 2007; Sueyoshi et al., 2008] the implementation of the learning process is integrated in to the trading simulator by using profit regression equations for each agent type. The variables in these profit equations are the α and β variables that are first computed from a historical dataset, and then used to adjust the bid prices and then are saved from each simulation round for trades that the agent has won. The signs of the coefficients on the α and β variables are used to decide which trading strategy to use and allows α and β to be re-computed for the next trading round. If the probability of reward does not exceed a threshold the agent does not make a trade. This threshold value is a parameter and can be adjusted by the user. The reward probability is shown to be a useful concept in TRAMAS by allowing agents to determine their next trading strategies.

2.10 Summary

This chapter discussed the related work to this research. There continues to be activity in this field that is generating new ideas and new approaches. Some of these technologies incorporate different estimation techniques for predictions and decision-making. A key deficit in the above studies is that they do not address the implications on market prices from different forecast beliefs, different personas and other market beliefs in the learning or price estimation process and how these relate within the trading context. The MAIS is the most advanced in the areas of learning and estimation and uses these concepts to assist agents in their decision-making.

The results of this thesis fit into four key areas discussed above. First, in the MAS area we extend the concept of agent' personas to the trading domain by showing how different personas and forecast beliefs can impact the way agents trade and specifically show how their trading behavior with other agents can influence prices. In order to gain insights into these influences we use data mining techniques such as visualization of data to determine trends and patterns in the buying and selling behaviours of agents that can provide interesting insights into how tomorrow's market may evolve. We extract the data using a structured querying language (SQL) and transform it based on the information needed and load it in a results table for visualization to the user.

Second, giving the user flexibility to construct different market models with agents with different personas and forecast beliefs then simulating these models and analyzing their differences is one way we combine both MAS and decision support. In the intelligent decision support area we build a new evolutionary decision support paradigm called T-Evolve* for trading. This paradigm allows users to simulate different market models and use the knowledge gained from the analysis of each model to build other models. This evolutionary nature of providing decision support for trading, to our knowledge, has not been pursued in the literature.

Third, in the area of validation, we validate the modeling constructs and results by industry experts. Within the trading domain, validation is more difficult because of time requirements from traders or analysts who are generally not responsive to providing input due to the competitive nature of the industry. However, we validate our approach from users that are industry veterans. A survey approach is used to gather input electronically. Analysis of the results shows very positive feedback from industry experts.

Fourth, incorporating personas and forecast beliefs into the machine learning functionality of agents helps to determine how trading strategies are chosen by agents. Agents can estimate the probability of reward of trades to determine whether to buy or sell with other agents. Knowledge accumulates after each simulation round and agents employ a logistic regression function to compute the probability of reward for future trades.

The next chapter shows how some of the concepts enable the development of the process and the technology.

CHAPTER 3: TRADING SIMULATION METHODOLOGY

3.1 Introduction

The TRAMAS technology adapts an evolutionary problem solving process to help users make better trading decisions with an awareness of the opportunities and threats in a market. The problem we are trying to solve is how to effectively provide decision support to traders in an environment of constant change such that their decisions to buy and sell result in lower risk and higher rewards. The class of problems we are trying to solve fall in the group of wicked problems [Rittel and Weber, 1973]. To solve the problem of making the optimal buy and sell decisions is based on the individual's belief of how tomorrows market may evolve, which may not be correct. In trading, ideas on how tomorrow's market may evolve is based on many factors that may or may not influence each other. If one believes that in tomorrow's market there will be more buyers than sellers, there are surely others who will believe the opposite just for the mere fact that others may believe something different. Factors such as weather conditions, personas and beliefs of people could influence market prices to behave one way one day, and completely differently another. There is no stopping rule that indicates that a market has been completely analysed; in fact, a user can analyse a market long enough until he has reached a level of confidence that the trading decisions he will make will be good enough or he may simply like one PMO better than another PMO based on gut feeling.

The analysis component of TRAMAS gives the user the flexibility to find patterns in the data that may show what a good trade is and what is a bad trade, there is no true or false. After choosing a trading decision, there is no guarantee that that decision will reap rewards or has the lowest risk because the decision is dependent on information at a certain point in time, and once the trade is made the actual market may also have changed. The set of solution alternatives (trading plans) are presented to the user who chooses the best one but this does not mean all the solution alternatives have been considered. It is ones judgement that decides to continue with generating other alternatives. The uniqueness in the solution alternatives is important in distinguishing between solution alternatives. The aim is not to find the truth but to improve the way the decision process is carried out in finding the best trading plan.

The methodology describes how the problem is solved by using an evolutionary decision support paradigm. As part of this paradigm, the user first constructs market models based on their beliefs about tomorrow. The choice of market components can be completely arbitrary or based on specific information about tomorrow. Second, the simulation of each market model produces a PMO. A PMO is one way a market may evolve; it is the output of one simulation, which is made up of a sequence of simulation rounds. Third, analysis of a PMO produces information that shows which trades are good and which trades are not good. These trades are recommendations based on the probability of reward from each trade: the higher the probability of reward the better the trade. Fourth, based on what the user learns from the analysis, he may choose another market model and re-run the simulation.

3.2 Intelligent Decision Support for Trading

3.2.1 Overview

What do we mean by providing support in this research? We touched on support concepts in the previous chapters. Formally, support here is multi-dimensional: (i) to facilitate understanding and structuring of the problem under investigation, (ii) to understand the information needs for making good decisions, (iii) to provide access to information that would otherwise be unavailable or difficult to obtain, (iv) to generate and pro-actively evaluate solution alternatives, (v) to prioritize alternatives by using explicit models that provides structure for particular decisions, and (vi) to offer explanation for proposed solution alternatives [Denzinger & Ruhe, 2004]. We will explain each dimension of support within the context of the three iterative phases.

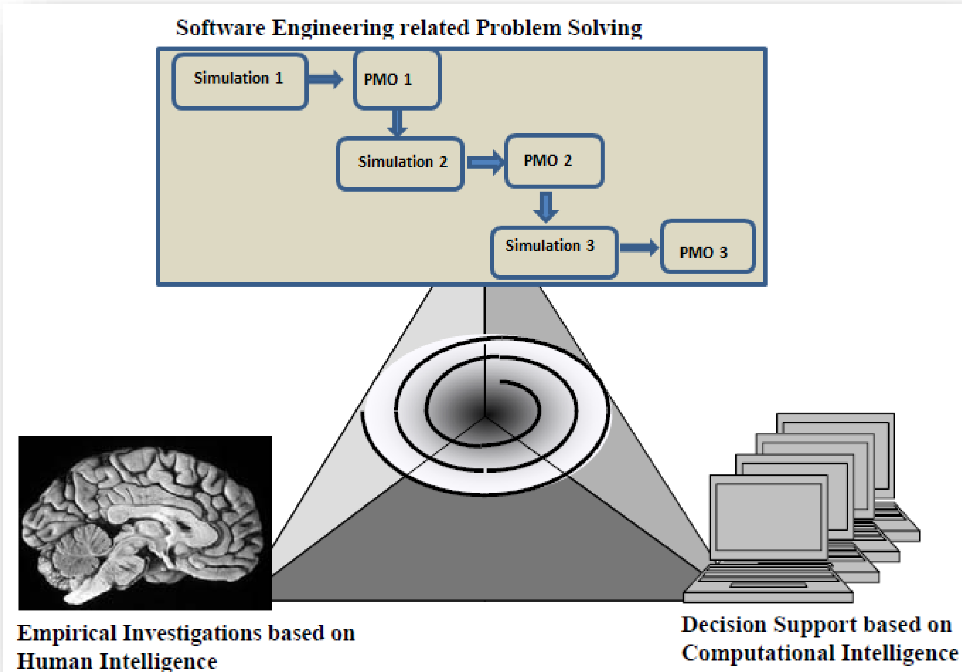


Figure 3-1: T-Evolve* Hybrid Process adapted from [Ruhe 2004]

The three phases within an evolutionary problem-solving context are shown in Figure 3-1. The modeling phase at the top is iterative processes of model building based on beliefs that changes get refined from the exploration (computational intelligence) phase. The consolidation phase (human intelligence) selects from the set of PMOs the best one based on certain criteria discussed below. The evolution part of the method is in the exploration phase of the T-Evolve* paradigm. Data visualization and sophisticated SQL queries extract patterns from the PMOs allowing the user to evaluate different trading plans; we will demonstrate this below.

Evaluation of the solution alternatives can follow concordance and discordance (CND) analysis that suggests that if there is no formal reason to prove or disprove some proposition D, then it is possible to use the argument “If there are enough facts supporting the proposition D (concordance) and there is no fact strongly opposing it (non-discordance), then we should accept D” [Bouyssou et al., 2000; Denzinger & Ruhe 2004]. Applying this type of reasoning in the consolidation phase can help in the selection. This evaluation method allows the user to compare different trading plans – if most trading plans indicate the same trade at the same time then there is evidence that this trade should be pursued. If there is little agreement on trades then likely these trades should not be pursued. Below provides an explanation of the phases.

3.2.2 The Three Phases

Phase 1 - Modeling: A representation of the changing real world that is appropriate for computationally intelligent based solutions that utilize solution technologies. This includes the choice of personas for all actors instantiated by agents, their forecast beliefs and data used by agents to predict future market prices. Other parameters such as which agents are buyers and sellers, and when they can trade and what function they use to make decisions are all defined here. In TRAMAS, this involves choosing a market model that is based on the users' belief about tomorrow. This model is suitable for computational intelligence solution technologies. A MAS approach is used to simulate the buying and selling behaviours of actual traders in the real-market.

Phase 2 – Exploration: Applying computational techniques that evaluate agents' trace data to determine patterns in trading behaviour. Data visualization is an important part of the exploration process because it allows the user to determine complicated patterns in the data that would be otherwise overlooked. Comparing the results from different PMOs facilitates the choice of the best trading plan. The best trading plan is based on the profits that each generates and the higher the profits the better the plan. While profits are a key determinant of the best trading plan, the user may choose to establish a trading plan that uses the suggested trades from different PMOs. In TRAMAS, exploration involves an intense examination or investigation of the solution space by visualizing the agents' trace data in order to gain deeper insights into the problem and its solution structure [Ruhe 2010]. Diversification among a set of solutions helps in broadening the understanding and narrowing the uncertainty inherent in the problem. In TRAMAS, analysis of trace data is performed by SQL queries to extract insights and intelligence about tomorrow's market.

Phase 3 – Consolidation: A human decision maker views the PMO results and investigates trading behaviour: when are agents making trades, what trades generate the most profits, where profits are the lowest, which agents are most active and which are least active. This helps in the understanding of the problem and motivates modification of the underlying components of the market model to establish a new market model. Typically, this helps to reduce the complexity of the problem for the next simulation. For the problem of trade planning in this thesis, the modeling activity includes choosing agents with particular personas, assigning forecast beliefs to agents, choosing the mathematical function from which agents compute the bidding prices, choosing which agents are buyers and sellers, when agents trade and what forecast data is used to generate price forecasts. In TRAMAS, consolidation requires human expertise, ideally, to evaluate the PMOs for insights into the selection of the best trading plan, or help in making refinements to the underlying market model. The consolidation phase involves pattern detection by visualizing trace data to determine trading behaviours of agents from different market models. This inherently aims to reduce the complexity of the problem space in helping to choose the best trading plan.

3.2.3 Evolution of PMOs

As a result of the planning process in constructing market models, different PMOs will be composed out of the market components such as different agent types, forecast data, estimation methods, amounts of buyers and sellers, and forecast beliefs. After each PMO, a re-planning can take place based on the outcomes such as how profits differ between agent type, which PMO makes the most profit, how profits differ between buyers and sellers, how profits differ between strategies used, etc. The number of PMOs is not fixed, and so a user can choose to evolve any combination of components for the next market model. By exploring the current PMO, helps a user to determine the next market model, in this way, the users continues to gain a better understanding about tomorrow's market. Can a user achieve a perfect understanding about tomorrow's market in this way? Perhaps, but more important here is not perfection, but rather the process of modeling, exploration and consolidation to finally choose the best trading plan from a PMO.

Expert judgement about the components may be important and could help in establishing a more realistic outcome of tomorrow, but in TRAMAS expert judgement is not required. The user should be able to quickly see the outcomes of the PMOs and help decide what types of trades he wants to make, or use this information to re-plan and re-generate another PMO. The flexibility in changing the components and re-generating a PMO offer a more realistic view of the evolving market place with constant changes in the above components.

3.2.4 Model Adjustment

There is no concept of a best or the right PMO because it is a result of users' beliefs about tomorrow, which may be wrong. As discussed below, the user can vary two parameters representing his beliefs about the forecast and the way he wants agents to behave. Specifically, we introduced an α_i parameter representing the forecast beliefs and a β_i parameter to represent the aggressiveness of agent *i*. We also introduced a parameter representing experience and inexperience (ζ_i). After the completion of each simulation, a PMO comprised of trace data is a snapshot of how a market may evolve. If we consider a PMO to be composed of many dimensions then information on each dimension can be extracted. For example, evaluating a market from the dimension of prices, positions and quantities, can help in the calculation of trading profits. We will discuss more about how $\alpha_i^t, \beta_i^t, \zeta_i^t$ are modified[2] by users based on their beliefs about tomorrow's market for each hour *t*.

3.2.5 The TRAMAS Decision-Making Process

[Ruhe 2010] defines six stages in the decision making process. In TRAMAS these are:

- **Define the problem:** How do the changes in forecast beliefs and personas impact tomorrow's market?
- **Define the alternatives:** Trade plans are alternatives generated from user chosen market models based on their beliefs about tomorrows market.
- **Evaluate the alternatives:** Each alternative is evaluated by the amount of profits it generated and the probability of reward for the trades. Looking for consistency in the probability of reward for trades is one way different trade plans may help the user decide which trades are better.

[2] ζ_t is a random variable chosen by the system. We decided to do this to simplify the analysis. In future research, this could also be a user chosen parameter based on users' beliefs or we may choose to intelligently determine this parameter by increasing it gradually during subsequent rounds to show that the longer an inexperienced trader is in the market, the more experienced he becomes.

- **Decide:** Choosing the most preferred trade plans based on selection, triaging or ranking to help decide the best trades to make or identify risks in the market to avoid.
- **Implement decision:** Based on the information gathered, the user can execute the trade(s) he feels have the highest probability of reward or decide that he does not want to trade if he feels the risk is too high.
- **Evaluate the decision:** If the trader decides to execute a trade, it can be evaluated by profit loss or gain based on some settlement process. Alternatively, if he did not trade, he can determine the opportunity cost of not trading and may consider adjusting his risk level for next time.

The appeal of evolutionary problem solving in trading is that it facilitates the evolution of problem comprehension that is consistent with evolving markets. The underlying principle to evolutionary problem solving is the three phases discussed above. These phases need not require explicit instructions on how to execute them; rather it is best to illustrate the operationalization of the phases.

The real world is used as the basis for the modeling formulation of the problem; formal methods are used to analytically generate PMOs from trace data. Formal methods encompass all methods and techniques in the context of the problem such as reasoning, simulation or optimization [Ruhe 2010]. Human experts provide feedback from evaluating the PMOs. This feedback is a necessary but not a sufficient condition for the success of this process [Ruhe 2010]. It is necessary for the creation of different market models. It is not sufficient because evolution and evolutionary processes may not lead to an actual realization of tomorrow's market. This is why we can only *potentially* realize profits in tomorrow's market due to uncertainties in the market, lack of knowledge of the real market and the likelihood that the market model may be an incorrect representation of how the market may actually evolve.

Figure 3-2 shows the T-Evolve* process steps' dependencies. The process is subdivided in to eight steps. It shows mandatory and optional steps, which are ordered in a sequential manner with feedback links between some of the steps.

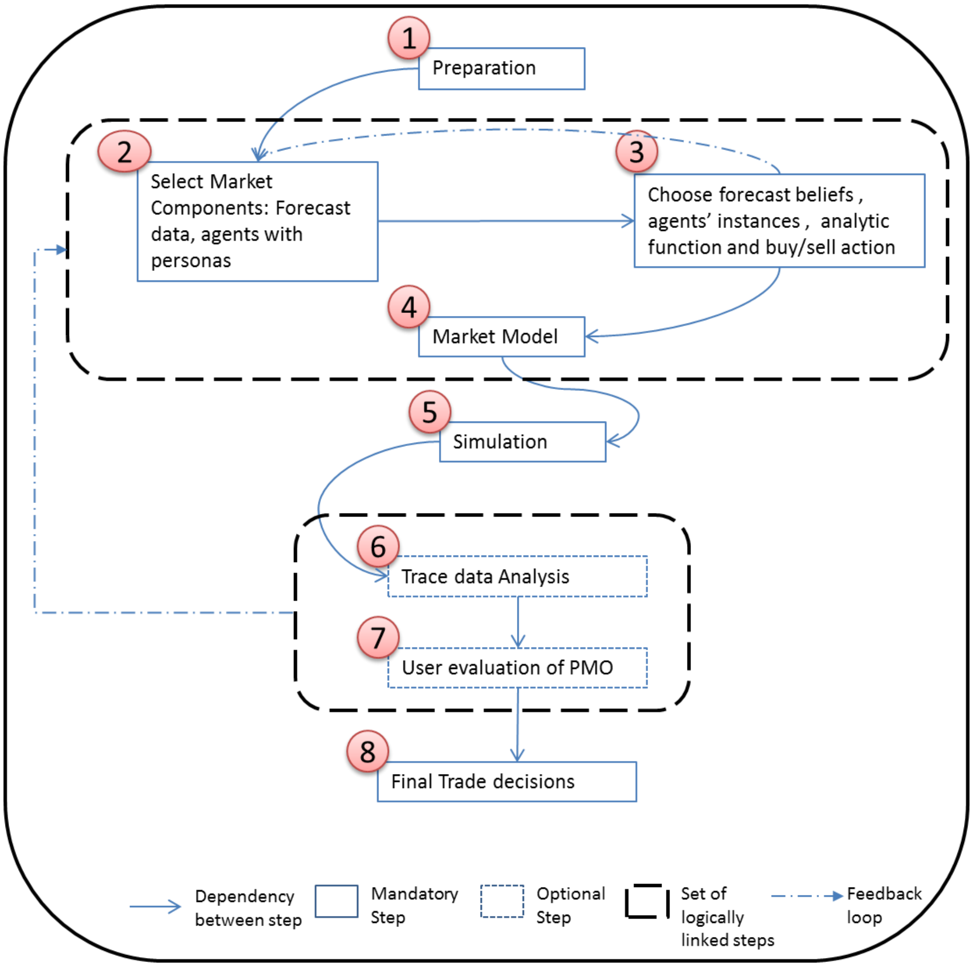


Figure 3-2 T-Evolve* Process Steps' Dependencies

For example, based on the analysis in step 6, it might be necessary to change the forecast beliefs for a certain agent persona or create more buyer agents than seller agents in step 3. In a more general sense, there is a likely possibility to return to steps 2-4 from steps 6-8. The description of the process steps follows a template presented in [Ruhe 2010]. Table 3-1 to Table 3-8 provide the description of the steps, system roles involved, input and output from the steps, the entry condition that must be met before starting the process, and the exit condition that must be met to terminate the process.

3.2.6 Step 1: Preparation

The first step in the process is the preparation step that defines the market to be analysed, along with forecast data components and actors' personas and key parameters for the activities to follow. Step 1 content is shown in Table 3-1.

Table 3-1: Key Details for Process Step 1

Item	Specification
Description	Based on the choice of financial market to study, specification of key market components that assist in determining how the market may evolve.
Roles Involved	User (Trader or Analyst)
Input	• Financial Market • Specific market information
Output	• Specification of financial market • Selection of market forecast data • Specification of actor personas
Entry criteria	The financial market to be studied is understood such that the fundamental sources of data that influence the market are identified.
Exit criteria	Agent personas and forecast data relevant to this financial market are chosen

3.2.7 Step 2: Select Market Components

The second step in the process is the selection of market components. The choice of forecast data and actors instantiated by agents with specific personas is chosen in this step. Step 2 content is shown in Table 3-2.

Table 3-2: Key Details for Process Step 2

Item	Specification
Description	Choice of forecast data and actors instantiated by agents with specific personas is specified.
Roles Involved	User (Trader or Analyst)
Input	• Agent personas • Forecast data
Output	• Chosen forecast data

	• Chosen actors instantiated with agents with specific personas
Entry criteria	• Financial market chosen • Forecast data identified • Personas identified
Exit criteria	Forecast data and agents with specific personas are selected

3.2.8 Step 3: Select Model Parameters

The third step in the process is the selection forecast beliefs, instances of agents, buy or sell action and analytical function (or estimation method) for agents bidding decisions. There is a feedback process at this step, where a user may choose to:

- Modify the forecast beliefs
- Add more buyers in the market
- Add more sellers in the market
- Modify the buying or selling actions
- Modify the analytical function used in predicting a market price or quantity
- Modify the personas
- Modify the forecast data

Step 3 content is shown in Table 3-3.

Table 3-3: Key Details for Process Step 3

Item	Specification
Description	This step specifies the forecast beliefs, instances of agents, buy or sell behaviour and analytical function to help agents make bidding choices.
Roles Involved	User (Trader or Analyst)
Input	• Selected agents with specific personas • Forecast data
Output	• Forecast beliefs available • Buy or sell actions • Instances of agents • Analytical function for agents
Entry criteria	• User selected agents • Forecast data chosen

	• Availability of forecast data
Exit criteria	• Forecast beliefs are chosen • Instance of agents are chosen • Buy or sell action type specified • Analytical function chosen

The feedback loop allows the user to re-plan and create different market model and regenerate a different PMO based on the outcomes from the current PMO. This loop is not mandatory.

3.2.9 Step 4: Committed Market Model

The fourth step in the process is the formulation of a market model. Because of the feedback loop in Step 3, a user commits to a market model in this step. Step 4 content is shown in Table 3-4.

Table 3-4: Key Details for Process Step 4

Item	Specification
Description	This step specifies the market model that is in agreement with the user's belief of how the market may evolve.
Roles Involved	User (Trader or Analyst)
Input	• Chosen forecast beliefs • Chosen instances for agent types • Chosen buying or selling actions • Chosen analytical function
Output	• Market model is available
Entry criteria	• Selected forecast beliefs • Selected instances • Selected buying or selling actions • Selected analytical function
Exit criteria	• User committed market model.

3.2.10 Step 5: Simulation

The fifth step in the process is the simulation of the market model that the user commits to in the previous step. Agents in the simulation use their analytical function to determine how they should bid into the market in round one. After round one, agents base their decisions on the reward potential of a trade that is determined by their bidding strategy. Section 3.4 will discuss the simulation process in detail. Step 5 content is shown in Table 3-5.

Table 3-5: Key Details for Process Step 5

Item	Specification
Description	A simulation of the market model is executed producing a PMO.
Roles Involved	User (Trader or Analyst)
Input	User committed market model as a result of Steps 1, 2, 3, 4.
Output	PMO is produced. Trace data that are subsequently queried for specific information, such as agent decisions, simulated market prices, profit generated by each agent, etc.
Entry criteria	Committed market model
Exit criteria	Existence of trace data

3.2.11 Step 6: Trace Data Analysis

The sixth step in the process is the analysis of trace data. All data is stored in database tables shown in 0. This data is queried for information specific to the user's needs. There is a core set of information such as simulated market prices for tomorrow, agents' bidding strategies, best trades ordered by their probability of reward, and profits for each agent type. There is of course more information that the user can extract. Step 6 content is shown in Table 3-6.

Table 3-6: Key Details for Process Step 6

Item	Specification
Description	This step analyzes trace data for information on the potential market outcomes.
Roles Involved	User (Trader or Analyst)
Input	Trace data
Output	Query results of trace data. The user queries these data for intelligence on the potential market outcomes. The presentation is a result set on a website.
Entry criteria	Availability of trace data.
Exit criteria	Evaluations of the PMO are conducted.

3.2.12 Step 7: Users' Evaluation of PMO

Intelligent decision-making is the process of searching and narrowing the solution space to the most likely set of candidates or the selection of the top ones [Ruhe 2010]. Users evaluate the PMO from different perspectives or beliefs based on their knowledge and experience of the market. The information such as the best trades to make, opportunities to go after and threat to avoid in the market should become apparent to the user in this step. If not, the feedback loop would be initiated. The optional Step 7 helps feed into the final decision. The content of the optional step 7 is shown in Table 3-7.

Table 3-7: Key Details for Process Step 7

Item	Specification
Description	Human judgement and experience help to identify the best trades, opportunities and threats that may take place in the market.
Roles Involved	User (Trader or Analyst)
Input	PMO
Output	Best trades, opportunities, and threats
Entry criteria	Availability of PMO.
Exit criteria	Defined trades, opportunities and threats.

3.2.13 Step 8: Final Trade Decision

Based upon the information gathered in steps 6 and 7, the final trade decision needs to be made. A user's beliefs about the future market have been explicitly incorporated into market models and associated PMOs generated. This increases the likelihood of better trading decisions with an awareness of the potential market opportunities and threats. The content of step 8 is shown in Table 3-8.

Table 3-8: Key Details for Process Step 8

Item	Specification
Description	Final trading decisions made based on the previous analysis and evaluations of PMOs.
Roles Involved	User (Trader or Analyst)
Input	Trace data (from Step 5) and their analysis and evaluations (Steps 6-7)

Output	Best trades identified
Entry criteria	Availability of all PMOs and their evaluations from former steps.
Exit criteria	Final trades chosen.

The iterative process is shown in Figure 3-3. Each iteration involves the choice of forecast data, agent personas, and agent parameters. Moving to the next iteration represents a change in the belief of the user about the market based on the learning from the previous PMO. For example, the learnings can be derived from determining which trades are the most profitable, at which times by which trader type. The user may wish to modify the next market model in a way that exploits the buying or selling behaviours of agents by putting more buyer agents in the market than seller agents or vice versa. Each PMO is diversified based on the profits and the probability of rewards of the trades. By focusing on the process to formulate and solve the right problem highlights the evolutionary aspect of problem solving that is the foundation of this iterative process.

It should be noted that there might not be any sense to the actual market model that the user chooses because markets are not always rational. Markets do not necessarily reward rational behaviour. For this reason, while market experience is important in choosing the right market model, there may be insights about the market that are gained from choosing the *wrong* model. Because there is no perfect way to choose the right market model, having a process in place that evaluates different market models is needed.

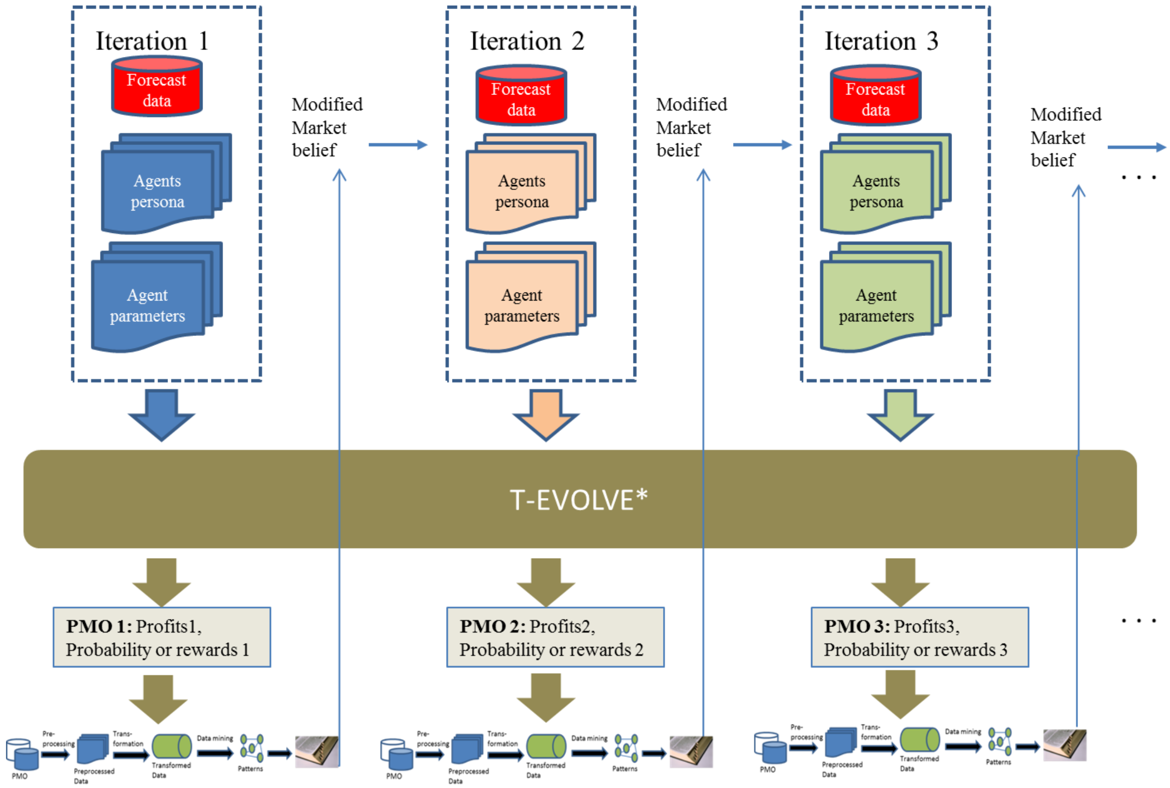


Figure 3-3: T-Evolve* Iterative Process

3.3 Market Models

The following Figure 3-4 shows a comparison of two different market models used in the analysis. Each of these models represent an iteration in the T-Evolve* process above. The selection of forecast data, agent personas and parameters represent steps 1-4 in Figure 3-2. The actual data from the simulation is stored in SQL tables shown in the Appendix.

In the model 450754, Figure 3-3, twelve agents are included in the market model: three agents are experienced aggressive agents who are buyers; three agents are experienced non-aggressive agents who are also buyers, three agents who are inexperienced aggressive agents who are sellers and three inexperienced non-aggressive agents who are also sellers. The first parameters row show that all agents believe in the load forecast. The second parameter row shows that all agents use the same estimation method. In the other model (527938) we may believe that there could be more buyers (8) than sellers (4) and those agents do not believe in the forecast. Why do we believe this? The belief is based on the outcomes in the previous model (450745) that may show that the market is not really split and likely to have more buyers than sellers. This could be due to extreme events that cause prices to rise; in this case buyers are likely to be more successful than sellers. While these two models, shown in the figure below, illustrate the differences in the types of market models that can be setup in TRAMAS, there are several more combinations that we will see in case study #2.

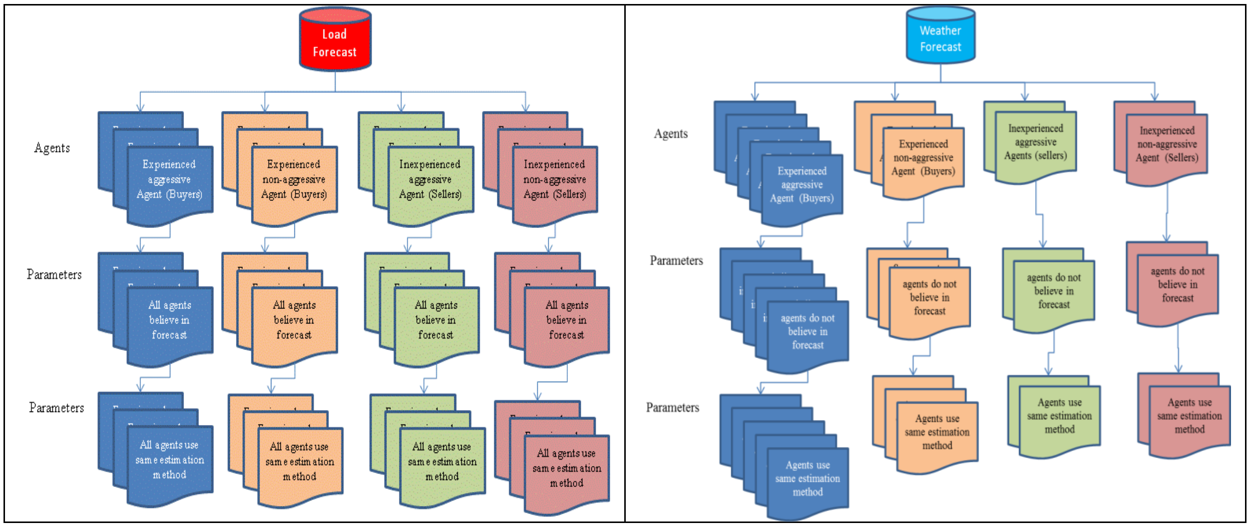


Figure 3-4: Market Models 450745 and 527938

The market models should be chosen for their diversity. The more diversified the models, the more varied the insights may be, which could provide the user with a greater understanding of the market. This could help to formulate better trading decisions and potentially reduce the risk from trading.

3.4 TRAMAS' Simulation Process

Figure 3-5 shows the simulation process for the market models, which is step 5 and 6 in Figure 3-2. Several key processes and activities are shown in Sections 5A-6 in the figure. Note that the numbering of the sections represents the steps 5 and 6 in Figure 3-2. Section 5A is the start of the simulation, it contains the accumulate knowledge process and the bid submission process. The knowledge process updates a knowledge database[3] that will act as input into the bid submission process. In the initial simulation round (r=1), the agents estimate a price and quantity for all hours using the forecast data and the price. In round one there is no price

[3] See Table 6-3: Accumulate Knowledge for the structure of this table.

adjustment using β, the prices are cleared in this round. In subsequent rounds, the prices will be adjusted according to a bidding strategy by accumulating knowledge from previous rounds, which is discussed in the bid submission process below. Once all agents have determined their price and quantity pairs, these values are submitted to the market-clearing agent who clears all the bids in Section 5B. Once the bids have been cleared, a settlement process is executed to determine the winners and losers from the trades in Section 5C. If an agent has won the trade, the strategy variables are updated and used in the next round. If the agent has lost, the strategy variables are not updated. All information is stored in the repository of agents' actions. In Section 6, after the user has ended the simulation, analysis can be done and presented to the user for evaluations that will lead into the final trading decisions.

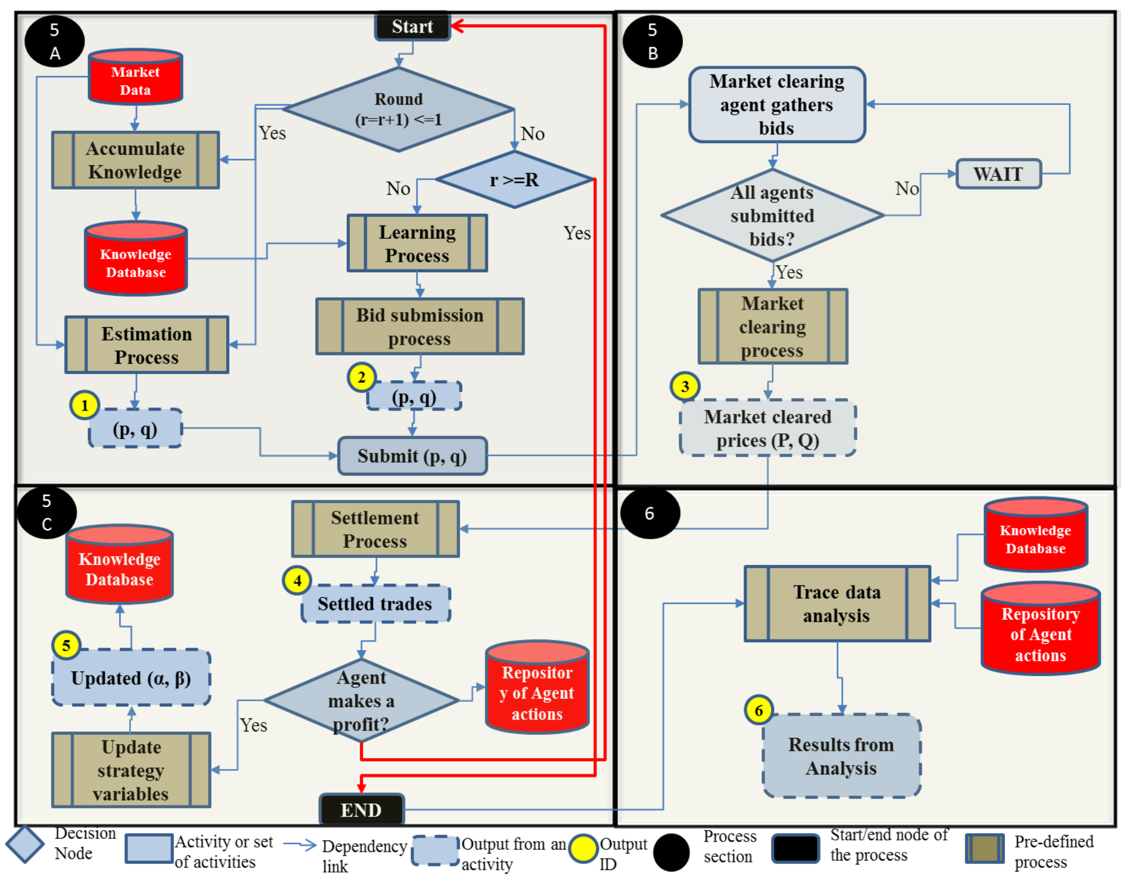


Figure 3-5: T-Evolve* Steps 5 and 6

3.4.1 Section 5A: Calculate Bids

There are two processes in this section: Accumulate Knowledge and Bid Submission Process. Each process is explained in the associated sub-sections.

Accumulate Knowledge Process

- **Objective**: Accumulate historical knowledge about $\prod, \alpha \; and \; \beta$, where $\prod$ is the profit reward equation. Once this data is generated, they are used in the profit regressions (shown below) to determine the probability of reward for a particular trade. Trading strategies are determined by the values of the coefficients on α and β.
- **Roles**: System
- **Input**: historical data on prices and forecasts
- **Output:** Time series data on $\prod, \boldsymbol{\alpha}, \boldsymbol{\beta}$ stored in a database. The $\boldsymbol{\alpha}$ **and** $\boldsymbol{\beta}$ are the historical values that will be used in the profit equations in Table 3-11 below. The dependent variable ($\prod$) is a binary variable that is determined by the logic in Table 3-9 and Table 3-10.
- **Detailed Description**:

The following is the learning process used by agents in TRAMAS. The key here is to accumulate knowledge on previous price differences between the real-time (RT) and day-ahead (DA) market prices to gain some knowledge on historical profits. Each step in the process is explained below:

Step A.1.1: Determine what forecast (i.e. Weather or Load) you will use for the learning of price dynamics. From the raw data on my research page[4] the data in Column D and F are the weather and load forecasts used in the analysis.

Step A.1.2: For a given current forecast, determine historical days that have a similar forecast. To do this, compare the averages of the days using the PPS formula and choose those historical days that exceed some predefined threshold number T, which can be a value between 0 and 1. A threshold value should be chosen such that the amount of days gives a reasonable sample of days that shows different price behaviours or several possible outcomes that could result.[5] A high T value would require a high degree of similarity and a low T would require a low degree of similarity. Let H^s be a set of similar days in the past. Based on the author's professional discussion with traders in the field, finding similar days as described above allows traders to

[4] Navigate to my research page to see the raw data: http://people.ucalgary.ca/~smaurice/phd_research_data.xls
[5] A standard rule of thumb is to have at least 30 days or more in H^s [Gujarati 1988].

isolate those days that would likely offer higher predictive power on what prices may be in the current market, than those days that are not similar to the current forecast.

Step A.1.3: For each day $d_k \in H^s$ let $DA_{k,t}^{c^{k-1}}$ be the day-ahead curve containing the market clearing prices and volumes from the successful bids and offers from buyers and sellers in the past, where c^{k-1} indicated day-ahead cleared (c) at day *k-1* for day *k*. Let $P_{t,k}^{RT}$ be the real-time price curve at day *k* for hours *t*=1... 24. Let $P_{t,k}^{c^{k-1}}$ and $Q_{t,k}^{c^{k-1}}$ be the cleared prices and volumes or quantity of electricity cleared at day *k-1* for day *k*. From the raw data[6], $P_{t,k}^{c}$ is column E (day-ahead price), and $P_{t,k}^{RT}$ is column C (real-time price).

Step A.1.4: Examine three cases for buyers and sellers for a given shape of the forecast as shown below in Table 3-9 and Table 3-10. These three cases help us to accumulate historical values for β that shows what the past price mark-ups were for a similar forecast. Buyers are rewarded when the real-time price ($P_{t,k}^{RT}$) is greater than the day-ahead price ($P_{t,k}^{c^{k-1}}$).

Table 3-9: Buyer Reward Cases

Case	Price Scenarios	Reward ($\prod_{t,k}$)	Price mark-up
B1	$P_{t,k}^{c^{k-1}} < P_{t,k}^{RT}$	1	$\frac{(P_{t,k}^{RT} - P_{t,k}^{c^{k-1}})}{P_{t,k}^{RT}} = \beta_{t,k}^{b}$
B2	$P_{t,k}^{c^{k-1}} = P_{t,k}^{RT}$	0	$\beta_{t,k}^{b} = 0$
B3	$P_{t,k}^{c^{k-1}} > P_{t,k}^{RT}$	0	$\frac{(P_{t,k}^{RT} - P_{t,k}^{c^{k-1}})}{P_{t,k}^{RT}} = -\beta_{t,k}^{b}$

The seller reward cases are the reverse of the buyer cases. As shown below, the seller can determine price mark-downs for similar forecasts. So using the example discussed above, had the value of electricity fallen to $90 in the real-time market the seller gains (**∏=1)** and the price mark-down is -0.1 or about 10%.

[6] Navigate to my research page to see the raw data: http://people.ucalgary.ca/~smaurice/phd_research_data.xls

Table 3-10: Seller Reward Cases

Case	Price Scenarios	Reward ($\prod_{t,k}$)	Price mark-down
S1	$P_{t,k}^{c^{k-1}} < P_{t,k}^{RT}$	0	$\frac{(P_{t,k}^{c^{k-1}} - P_{t,k}^{RT})}{P_{t,k}^{RT}} = -\beta_{t,k}^{s}$
S2	$P_{t,k}^{c^{k-1}} = P_{t,k}^{RT}$	0	$\beta_{t,k}^{s} = 0$
S3	$P_{t,k}^{c^{k-1}} > P_{t,k}^{RT}$	1	$\frac{(P_{t,k}^{c^{k-1}} - P_{t,k}^{RT})}{P_{t,k}^{RT}} = \beta_{t,k}^{s}$

Note that the $\alpha_{t,k}$ values are the differences between the user modified forecast and the real forecast divided by the real forecast, such that the difference will signify percentage decrease or increase.

Step A.1.5: Store each $\prod_{t,k}$, $\alpha_{t,k}$ *and* $\beta_{t,k}^{s\ or\ b}$ in a database table.
Using the historical information about $\prod_{t,k}$, $\alpha_{t,k}$, and $\beta_{t,k}$ agents can decide in a systematic way how much to bid into the market based on previous rewards and losses as represented by $\prod_{t,k}$. The values of $\alpha_{t,k}$ and $\beta_{t,k}$ act as independent variables in the profit equations discussed in the learning process next.

Learning Process

- **Objective**: A learning process that estimates the agent's profit or reward equation, defined below, to determine the coefficient values: (c_1, c_2). These coefficients play a key role in the agents trading strategies that will be discussed below.
- **Roles**: Agent
- **Input**: $\prod_{t,k}$, $\alpha_{t,k}$ *and* $\beta_{t,k}^{s\ or\ b}$
- **Output**: (c_1, c_2) and probability of reward.
- **Detailed Description**:

Following [Sueyoshi et al., 2005; Sueyoshi et al., 2008] a logistic regression (logit) model will be used to predict the probability of rewards; the formulation of this estimation model are shown in Eqs. (3-1) - (3-5). A logistic regression is a standard statistical model used when the dependent variable is dichotomous, taking values between 0-1; a cumulative distribution function (CDF) can be used to model such regressions because it always lies between 0-1 and are commonly chosen to represent 0-1 response models [Gujarati, 1988, p.480].

The profit regression equations are formulated for each type of agent as shown in Table 3-11. These equations will be critical for the determination of bidding strategies as well as to determine the probability of rewards. Consider this functional form from a theoretical perspective. A trader's profits will be based on his belief of the forecast and the price he bids into the market. If I was to correctly guess the shape of the forecast (α) and bid the right price into the market that is adjusted by β, as a buyer or seller, the probabilities of reward should be higher because of the higher likelihood of winning the trade. The profit equations allow agents to adjust their trading strategies by learning from past bidding behaviours. This learning is captured by c_1 and c_2.

Table 3-11: Profit Equations

Label	Profit regressions
PR1	$\prod_{i,t,k}^{a} = c_{i0}^{a} + c_{1i}^{a}\alpha_{\mathrm{it,k}}^{a} + c_{2i}^{a}\beta_{it,k}^{a} + \varepsilon_{it,k}^{a}$
PR2	$\prod_{i,t,k}^{na} = c_{i0}^{na} + c_{1i}^{na}\alpha_{\mathrm{it,k}}^{na} + c_{2i}^{na}\beta_{it,k}^{na} + \varepsilon_{it,k}^{na}$
PR3	$\prod_{j,t,k}^{a} = c_{j0}^{a} + c_{1j}^{a}\alpha_{\mathrm{jt,k}}^{a} + c_{2j}^{a}\beta_{jt,k}^{a} + \varepsilon_{jt,k}^{a}$
PR4	$\prod_{j,t,k}^{na} = c_{j0}^{na} + c_{1j}^{na}\alpha_{\mathrm{jt,k}}^{na} + c_{2j}^{na}\beta_{jt,k}^{na} + \varepsilon_{jt,k}^{na}$

From the estimated profit equations, we can derive the probability of reward (P) for any agent, using the cumulative logistic distribution shown in Eq. (3-1) [Sueyoshi et al., 2005]. The reason the logistic model is chosen is because it allows us to estimate a model where the response variables, in Table 3-11, are binary. Specifically, in PR1-PR4 reward (=1) or no reward (=0) as computed in Table 3-9 and Table 3-10, which allows the estimated results to be bounded by 0 and 1 due to the logistic distribution, allowing us to interpret the estimated results as probabilities of reward [Sueyoshi et al., 2005]. If we were to choose a linear regression formulation, and not a logistic formulation, the estimated values would not be bound by 0-1 because the response variable would be a continuous variable, as opposed to binary, and so cannot be interpreted as probabilities. The formulations below in Eq. (3-1)-(3-5) show how the profits equations can be converted to a logistic model for estimation so that it is possible for us to compute the probability of a reward. For example, let P_i^a be the probability of reward for an aggressive buyer agent, then:

$$\boldsymbol{P_{i,t,k}^a} = \boldsymbol{E}(\prod_{i,t,k}^{a} = \mathbf{1}) = \frac{\mathbf{1}}{\mathbf{1}+e^{-(c_{i0}^a + c_{1i}^a \alpha_{it,k}^a + c_{2i}^a \beta_{it,k}^a)}} \tag{3-1}$$

where $\prod_{i,t,k}^{a} = 1$ means agent earned a reward. $P_{i,t,k}^a$ ranges between 0 and 1. However, because in Eq. (3-1) the model is nonlinear in both the c's and $\alpha_{i,t,k}^a$ and $\beta_{i,t,k}^a$ linear estimation methods like ordinary least squares cannot be used [Gujarati, 1988]. But this can be rectified as follows [ibid]. Since if $P_{i,t,k}^a$ is the probability of a reward, then $(1 - P_{i,t,k}^a)$ is the probability of no reward. For ease of analysis we can write (3-1) as:

$$P_{i,t,k}^a = \frac{1}{1+e^{-Z_{i,t,k}}} \tag{3-2}$$

where $Z_{i,t,k} = c_{i0}^a + c_{1i}^a \alpha_{it,k}^a + c_{2i}^a \beta_{it,k}^a$. And,

$$\left(1 - P_{i,t,k}^a\right) = \frac{1}{1+e^{Z_{i,t,k}}} \tag{3-3}$$

Eq. (3-3) is the probability of not earning a reward. Then the odds ratio of earning a reward is

$$\frac{P_{i,t,k}^a}{1-P_{i,t,k}^a} = \frac{1+e^{Z_{it,k}}}{1+e^{-Z_{it,k}}} = e^{Z_i} \tag{3-4}$$

By taking the natural log of both sides of Eq. (3-4), we can create a linear estimation equation:

$$L_{i,t,k} = \ln\left(\frac{P_{i,t,k}^a}{1-P_{i,t,k}^a}\right) = Z_i = c_{i0}^a + c_{1i}^a \alpha_{i,t,k}^a + c_{2i}^a \beta_{i,t,k}^a + \varepsilon_{i,t,k}^a \tag{3-5}$$

Now $L_{i,t,k}$ is not only linear in $\alpha_{i,t,k}^a$ and $\beta_{i,t,k}^a$ but also in the parameters, c_{1i}^a and c_{2i}^a. Eq. (3-5) is called the logit model [Gujarati, 1988]. The estimation of Eq. (3-5) allows agents to choose their bidding strategies based on the past learnings captured in c_{1i}^a and c_{2i}^a as will be discussed below.

A similar formulation follows for other personas. To simulate experience and inexperience in the model, a noise term is added $0 < \zeta_t \leq 1$ in the profit equations. If an agent is experienced $\zeta_t = 1$, otherwise it ranges from $0 < \zeta_t < 1$ for inexperienced agents. Put another way, ζ_t injects randomness or noise in the choice of strategies. For example, we simply multiply both $\alpha^{a}_{it,k}$and $\beta^{a}_{it,k}$ with ζ_t. Other methods could likely be used, but in an effort to keep the analysis simple this was our approach. [Kandori et al., 2008] uses a similar noise term in their logit model and state that when the noise term acts as a representation of mistakes, an agent who makes fewer mistakes receives a higher utility in the long run. Other research has used a noise term in their model to simulate effects of learning [Fudenberg & Harris 1992].

Estimation Process

The buyer and seller must bid into the market a price and quantity combination that they want to buy or sell, respectively. Therefore, it must predict a price and volume that it thinks will likely come true in tomorrow's market. The estimation process occurs only in the first round of the simulation. This is because in subsequent rounds, the learning process allows agents to adjust their previous round bids based on the probability of rewards that are likely to be generated. We discuss this adjustment in subsequent rounds in the bidding process below.

The estimation process can also be considered as the first learning process of how prices are influenced by the forecasts. The estimation process in round 1 allows all agents to establish a price forecast based on historical prices, which are publicly available. The forecast used will be the actual forecasts (if agents believe in it) or the modified forecast (if they do not believe in it).

The user has at its disposal two forecasting methods that can be assigned to agents. Two methods, currently, available in TRAMAS are:

1) Regression analysis (RA)

2) Neural networks (NN)

The choice of the method can be chosen based on what others may be using. Specifically, it can be used to determine how others may bid into the market had they used one of these methods. The belief on what forecasting method others may be using can be used to learn the impacts on the market from these methods. This may be important because different methods could give different price and quantity predictions that a user can further use for market insights and help to guide the types of trades they make. Given the load or weather forecast as chosen by the user, the following steps show how historical data is chosen for predictions. The objective here is to go back in the historical database[7] to find similar forecasts and use that to predict prices. Our approach gives the user the flexibility to modify the original forecast as he sees fit.

Step A.2.1: User determines if he believes in the forecast or not, if not, he modifies the original forecast by choosing α_{jt} in Eq. (3-6):

$$F'_{jt} = F_t * (1 + \alpha_{jt}), \tag{3-6}$$

F'_{jt} is then used to generate a forecast in step 3 below. The choice of α_{jt} is the user's forecast belief. If he feels that the forecast is not correct then the values of α_{jt} will modify the original forecast (F_t) otherwise he will not. The next step takes the modified forecast and goes back in the historical database to find similar forecasts.

Step A.2.2: Evaluate the historical forecast and determine what past days had a similar forecast outcome: $d_1, .., d_k \dots d_n$, where $k \leq n$, where the subscripts represent days. To determine the most similar days we use the distance for each hour then take the average for the day. Therefore, we have one number representing the average for that day; if this number equals or exceeds a threshold value then it is accepted, otherwise it is not (we use a threshold of 80%). For example, from the complete set of days we may get (d_5, d_8, d_{56}), which says that historical days 5, 8 and 56 have the most similar conditions, these days are used in the analysis in the step below.

Step A.2.3: Once the similar forecasts are determined then each agent estimates prices for each hour using one of the two estimation methods based on the type of forecast used. The following Eqs. (3-7) and (3-8) show typical linear regression models:

a) Regression Model for Weather Forecast in Eq. (3-7):

$$\text{Model:} \quad p_{jt}^n = \Psi_{1j} + \Theta_{1j} F_{jt}^{\prime,n} + e_{jt}^n, \tag{3-7}$$

where t =1...24 and p_{jt}^n is a vector of real-time prices for the similar days n, $F_{jt}^{\prime,n}$ is the weather forecast for the similar days, Ψ_{1j} and Θ_{1j} are the constant and slope regression coefficients, respectively. The method of estimation of the coefficients is done by the standard ordinary least squares (OLS) method, which minimizes the sum of squared errors e_{jt}^n and e_{it}^n by taking the

[7] Navigate to my research page for the data used: http://people.ucalgary.ca/~smaurice/phd_research_data.xls

difference between the dependent and independent variables and finding Ψ and Θ at the minimum point. Note we are running twenty-four regressions for every hour. We do this because each hour of electricity consumption is not the same as the previous hour. For example, off-peak hours are much different than on-peak hours due to differences in human behaviours during these times. Similarly,

b) Regression Model for Load Forecast in Eq. (3-8):

$$\text{Model: } p_{it}^{n} = \Theta_{1i} F_{it}^{\prime,n} + e_{it}^{n}, \qquad (3\text{-}8)$$

The only difference from the weather forecast model other than the data is the absence of the intercept term Ψ_1, because if there is no load to supply in the market, prices will be zero. This regression model is called a regression through the origin [Gujarati, 1988].

c) NN model is another method available to users to estimate the real-time price. TRAMAS uses a feedforward backpropagation network with five nodes in the hidden layer, with a tangent sigmoid as a transfer function in the hidden layer and a linear function for the output layer; the training function is a gradient descent with momentum backpropagation function. We train the network with the following parameters: the number of epochs is 500, the learning rate is 0.001% and the momentum is 0.6. What is important is to see how different estimation methods affect prices and how these are incorporated in the agent decision functions. It is out of the scope of this thesis to discuss in-depth neural networks. We used standard parameters without extensive calibration; future research could focus more on the estimation methods to allow for a more strategic selection of parameters. We could have easily used other estimation methods. We used the standard MATLAB neural network function (newff) to build the feedforward backpropagation network. Specifically, as input into the newff function, the input vector was the forecast, and the target vector were the historical real-time prices. The transfer function used for the hidden layers was the default 'tansig' function, and for the output layer we used 'purelin'. The network training function was 'traingdm'.

Up to this point we have shown how a user can modify the forecast based on his beliefs and how similar historical forecasts can be determined based on how similar they are to the modified forecast. We have shown and discussed how similarity is determined and using some threshold value what days are considered in the estimation process. We feel this to be a simple and sensible approach because rather than using all historical data, by matching the shape of the forecast and using just those days that are similar allows for less noise in the sample from days that are not similar, which could also affect the price estimations by making them less precise.

While the above uses forecast beliefs to estimate prices, the next steps add in agent personas and show how this modifies the price further before it is finally submitted to the market.

Step A.2.4: Once the price is estimated, the agent can modify it based on its persona. For aggressive buyers, rather than trying to undercut competitors, they will try to bid the highest price possible as in Eq. (3-9):

$$p_{jt}^{a(*)} = \mathrm{p}_{\mathrm{jt}}^{\mathrm{a}} + (p_{jt}^{a} * \beta_{jt}^{a}) \tag{3-9}$$

Note that the bidding process is anonymous so it may be that there is no seller willing to sell to an aggressive buyer because another buyer in the market has offered an even higher price. In order to determine quantity, we can recall that the slope of the demand curve (in most cases) is $\varphi < 0$. The quantity bid by buyers is based on whether the previous hour price was less or greater than the current price, if the previous hour price was greater than current price, then increase quantity, else decrease it:[8]

$$\boldsymbol{q_{jt}^{a(*)}} = \begin{cases} \boldsymbol{q_{jt}^{a(*)} * \left(1 + \beta_{jt}^{a}\right),\ p_{jt-1}^{a(*)} > p_{jt}^{a(*)}} \\ \boldsymbol{q_{jt}^{a(*)} * \left(1 - \beta_{jt}^{a}\right),\ p_{jt-1}^{a(*)} < p_{jt}^{a(*)}} \end{cases}$$

(3-10)

Similarly for non-aggressive buyer

$$\boldsymbol{q_{jt}^{na(*)}} = \begin{cases} \boldsymbol{q_{jt}^{na(*)} * \left(1 + \beta_{jt}^{na}\right),\ p_{jt-1}^{na(*)} > p_{jt}^{na(*)}} \\ \boldsymbol{q_{jt}^{na(*)} * \left(1 - \beta_{jt}^{na}\right),\ p_{jt-1}^{na(*)} < p_{jt}^{na(*)}} \end{cases}$$

(3-11)

In order to attract buyers, an aggressive seller will try to undercut other sellers by offering a low premium in the selling price, whereas a non-aggressive seller may not necessarily do so. To

[8] Where $p_{jt-1}^{a(*)}$ = 0 if t=1, similar for other non-aggressive variables when t=1.

model this behaviour, we assume that an aggressive seller will price closer to the estimated price (p_{it}^{a}) – the procedure a supplier uses to determine the price estimate is discussed below:

$$p_{it}^{a(*)} = p_{it}^{a} + (p_{it}^{a} * \beta_{it}^{a}) \tag{3-12}$$

Similarly,

$$p_{it}^{na(*)} = p_{it}^{na} + (p_{it}^{na} * \beta_{it}^{na}) \tag{3-13}$$

The seller must also decide the amount of quantity it will offer. Based on the forecast in **Step A.2.1:** Let $\mu_{it} = \frac{LF_{it}'}{LF_{it+1}'}$ to get the shape, then

$$q_{it}^{a(*)} = \frac{p_{it}^{a(*)}}{\vartheta} * \mu_{it} \tag{3-14}$$

Recall that ϑ is the slope of the supply curve ($\vartheta > 0$). Similarly, for non-aggressive agents

$$q_{it}^{na(*)} = \frac{p_{it}^{na(*)}}{\vartheta} * \mu_{it} \tag{3-15}$$

At this point agents have determined the prices and quantities they would bid into the market based on their forecast beliefs and personas. Showing and analysing the effects from the combination of forecast beliefs and agents' personas on market cleared prices are one of the core contributions of this thesis.

Step A.2.6: Buyer agent submits the bids ($p_{jt}^{a(*)}, q_{jt}^{a(*)}$) or ($p_{jt}^{na(*)}, q_{jt}^{na(*)}$), and seller agent submits ($p_{it}^{a(*)}, q_{it}^{a(*)}$) or ($p_{it}^{na(*)}, q_{it}^{na(*)}$) in the market. These starred price and quantity pairs for each hour (*t*) for aggressive (*a*), non-aggressive (*na*) and buyers (*j*) and seller (*i*) contain the influence of forecast beliefs and personas. All submitted bids by all agents are cleared by a market clearing agent. The cleared bids create a market cleared price curve for each hour (1-24), these curves show the results of the buy and sell bids that have been matched by the market clearing agent during each simulation round. The market clearing process below will discuss this process in detail. So, after all of these steps, A.2.1-A.2.6, every agent has the prices for each hour they want to bid.

During other iterations, as shown in the T-Evolve* process, different market cleared price curves will be generated based on different market models following steps 1-5 in the Figure 3-2.

Analysis of the trace data, steps 6-8, will help to provide information to the user as to which trades generated the most profits and when? Which trades generated the least profits and when? Did buyers make more profits then sellers? Etc.

Bid Submission Process

This process executes in subsequent rounds of the simulation (round > 1). It uses the estimated prices and computed quantities as input in the process.

- **Objective**: Determine the markup or markdown amount for prices to bid into the market.
- **Roles**: Agent
- **Input**: $(p_{jt}^{a}, p_{jt}^{na}, p_{it}^{a}, p_{it}^{na})$, pairs for every hour: *t=1..,24*
- **Output**: $(p_{jt}^{a(*)}, q_{jt}^{a(*)})$, $(p_{it}^{a(*)}, q_{it}^{a(*)}), (p_{jt}^{na(*)}, q_{jt}^{na(*)})$, $(p_{it}^{na(*)}, q_{it}^{na(*)})$
- **Detailed Description**:

TRAMAS incorporates a learning process that uses the results from the previous rounds of trade as input into the next round. Each agent's α and β are saved in a knowledge database[9] if an agent won or lost the trade, and the profit equations are re-estimated, as discussed above, to generate the probability of rewards; since α is not used in the price adjustment, we focus on the β parameter. In this way, an agent can accumulate knowledge of which previous values of β led to winning trades in order to adjust the prices for potentially greater probability of winning in future trades.

Given the above profit equations' coefficients we can determine the bidding strategies for both buyers and sellers. Each of the profit equations provides eight strategy variables and eight strategy coefficients shown in Table 3-12 below. The PR1-PR4 indicates the grouping of the variables and coefficients for agent types.

Table 3-12: Profit Equations: Strategy Variables and Coefficients

PR1		PR2		PR3		PR4	
Strategy Variables	Strategy Coefficients	**Strategy Variables**	Strategy Coefficients	**Strategy Variables**	Strategy Coefficients	**Strategy Variables**	Strategy Coefficients
α_{it}^{a}	$\hat{c}_{1i}^{a}$	α_{it}^{na}	$\hat{c}_{1i}^{na}$	α_{jt}^{a}	$\hat{c}_{1j}^{a}$	α_{jt}^{na}	$\hat{c}_{1j}^{na}$
β_{it}^{a}	$\hat{c}_{2i}^{a}$	β_{it}^{na}	$\hat{c}_{2i}^{na}$	β_{jt}^{a}	$\hat{c}_{2j}^{a}$	β_{jt}^{na}	$\hat{c}_{2j}^{na}$

[9] The structure of this table called ACCUMULATE_KNOWLEDGE, can be seen in Appendix C .

Each set of strategy coefficients determine the direction in the change of the strategy variables. For example, for aggressive sellers, if $\frac{\partial \Pi_i^a}{\partial \boldsymbol{\beta}_{it}^a} = \hat{c}_{2i}^a < 0$, then β_{it}^a should be decreased to increase the probability of rewards; if $\hat{c}_{2i}^a > 0$, then β_{it}^a should be increased to increase the probability of rewards, etc. The procedure to modify the strategy variables to improve the chances to win a trade can be described below in a similar fashion to [Sueyoshi et al., 2005; Sueyoshi et al., 2008]; we can define 36 different bidding strategies in the following steps that build on the work by the previous author with steps A.3.1 –A.3.6 being similar to the steps in [Sueyoshi et al., 2005; Sueyoshi et al., 2008]. What we have changed in this process is to show how forecast beliefs and personas can be used to extend the bidding strategies beyond the nine (9) used by [Sueyoshi et al., 2005; Sueyoshi et al., 2008] to thirty-six (36) different strategies. The formulations below are the author's own, adapted from the initial work of Sueyoshi.

Step A.3.1: Initialize the decision variables for each agent type:

a) $(\alpha_{\mathrm{it}}^{\mathrm{a,c}}, \beta_{it}^{a,c})$

b) $(\alpha_{\mathrm{it}}^{\mathrm{na,c}}, \beta_{it}^{na,c})$

c) $(\alpha_{\mathrm{jt}}^{\mathrm{a,c}}, \beta_{jt}^{a,c})$

d) $(\alpha_{\mathrm{jt}}^{\mathrm{na,c}}, \beta_{jt}^{na,c})$

For the initialized variables specify the upper and lower bound constraints on the variables such as:

a.1) $\alpha_{\mathrm{it}}^{\mathrm{a,L}} \leq \alpha_{\mathrm{it}}^{\mathrm{a,c}} \leq \alpha_{\mathrm{it}}^{\mathrm{a,U}}$
a.2) $\beta_{it}^{a,L} \leq \beta_{it}^{a,c} \leq \beta_{it}^{a,U}$

b.1) $\alpha_{\mathrm{it}}^{\mathrm{na,L}} \leq \alpha_{\mathrm{it}}^{\mathrm{na,c}} \leq \alpha_{\mathrm{it}}^{\mathrm{na,U}}$
b.2) $\beta_{it}^{na,L} \leq \beta_{it}^{na,c} \leq \beta_{it}^{na,U}$

c.1) $\alpha_{\mathrm{jt}}^{\mathrm{a,L}} \leq \alpha_{\mathrm{jt}}^{\mathrm{a,c}} \leq \alpha_{\mathrm{jt}}^{\mathrm{a,U}}$
c.2) $\beta_{jt}^{a,L} \leq \beta_{jt}^{a,c} \leq \beta_{jt}^{a,U}$

d.1) $\alpha_{\mathrm{jt}}^{\mathrm{na,L}} \leq \alpha_{\mathrm{jt}}^{\mathrm{na,c}} \leq \alpha_{\mathrm{jt}}^{\mathrm{na,U}}$
d.2) $\beta_{jt}^{na,L} \leq \beta_{jt}^{na,c} \leq \beta_{jt}^{na,U}$

If this is the first iteration in the learning process, then use the average historical values for $\alpha_{it}^{a,c}$, $\beta_{it}^{a,c}$ and similarly for other types and specify the lower bound values to be 0 and the upper bound values as 1. Otherwise, set the upper and lower bound values to be the new values under a winning trade.

Step A.3.2: Estimate the profit equations in Table 3-11 using data from the knowledge accumulation process to get values for strategy coefficients.

Step A.3.3: Based on the parameter estimates in Step A.3.2, agents in TRAMAS are able to change the appropriate strategy variables from one of the 36 rules summarized below in Table 3-13. Each of the rules in Table 3-13 is a representation of adaptive learning which focuses on past rewards attained from previous formulations of strategy variables. Specifically, in Rule 1, if the strategy coefficients are $\hat{c}_{1i}^{a} > 0$ & $\hat{c}_{2i}^{a} > 0$, this means that if α_{it}^{a} increases, the log of the odds of earning a reward goes up by $\hat{c}_{1i}^{a}$. Similarly, if β_{it}^{a} increases, the log of the odds ratio in favour of earning a reward increases $\hat{c}_{2i}^{a}$. To compute the probability of earning a reward simply take the antilog of (3-5) to get:

$$\frac{P_{i,t,k}^{a}}{1-P_{i,t,k}^{a}} = e^{Z_i} \tag{3-16}$$

Solving for $P_{i,t,k}^{a}$ we get

$$P_{i,t,k}^{a} = \frac{e^{Z_i}}{1+e^{Z_i}} \tag{3-17}$$

The antecedent of each rule can be interpreted in a similar manner as done from Rule 1. With respect to the consequent of Rule 1: $(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}\}$ consider Figure 3-6 below which describes the learning process for strategic bidding by agents.

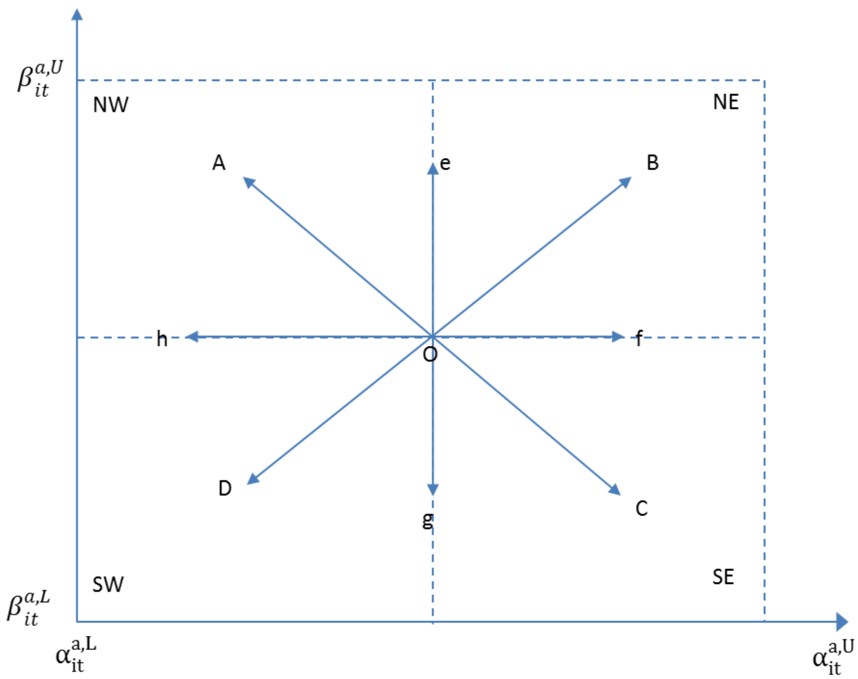


Figure 3-6: Visualizing Strategy Variables for Aggressive Persona

The strategy variables, α and β, can be shown visually in Figure 3-6 and their values are expressed on A, B, C, D; if one of them is zero then they are expressed on e, f, g, and h [Sueyoshi et al., 2005]. For example, for an aggressive persona, the initial strategy variables $(\alpha_{it}^{a,c}, \beta_{it}^{a,c})$ will be located at point O. The value of ½ in step 3 is a reasonable starting point as it indicates the center of each area that is shaped by the upper and lower bounds [Sueyoshi et al., 2005]; they also claim that there is no theoretical justification for using ½ but that ½ results in a faster convergence in the learning process for β, than ¼ or ¾. However, this could also be an area for future research to determine how this value affects the convergence rate to some optimal β value. During the exploration process in T-Evolve*, one may be able to adjust this value more appropriately in the next iteration. Specifically, as part of the preparation step 1 in the T-Evolve* process, this variable could be adjusted to see if it provides different insights into how differently the market cleared prices are generated from values in the previous iterations.

In Rule 1, the likelihood of earning a reward requires that the strategy variables lie in the NW quadrant. Based on the coefficient values, increases or decreases in the strategy variables provide the agents the best bidding strategies for earning a reward. While a reward is not guaranteed by this method, the strategy variables that result in a reward are used again in the next simulation round, otherwise new ones are computed. In this way, agents of different persona types and forecast beliefs have a systematic way to adjust their bid prices by choosing the best possible strategies through this adaptive learning process. This also is one way to provide increased transparency in trading, especially when traders incur losses. For example, trade losses can be traced back to the strategy used, which a trader may choose to avoid in future trades. Also, traders can adjust their trading behaviour by requiring a higher probability of reward from the strategy variables, or be more risk neutral by requiring a lower probability of reward.

For Rule 6, $\hat{c}_{1i}^{a} = 0$ & $\hat{c}_{2i}^{a} = 0$, the strategy is to stay at the mid-point $(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c}, \beta_{it}^{a,c}\}$ values because any change in the strategy variables results in zero odds of earning a reward. For Rule 5, $\hat{c}_{1i}^{a} < 0$ & $\hat{c}_{2i}^{a} = 0$, a decrease in α_{it}^{a} will result in an increase in the odds of earning a reward, while no change in β_{it}^{a} is suggested or simply stay at $\beta_{it}^{a,c}$. In Figure 3-6 this would mean we are on the h line. For Rule 9, $\hat{c}_{1i}^{a} > 0$ & $\hat{c}_{2i}^{a} < 0$, increase α_{it}^{a} and decrease β_{it}^{a} to achieve an increase in the log odds ratio of earning a reward. In Figure 3-6 this means we would be on C. Similarly for Rule 30, $\hat{c}_{1j}^{na} > 0$ & $\hat{c}_{2j}^{na} = 0$, for non-aggressive agents buyers, $(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} + \frac{1}{2}\lambda_{j}^{na}, \beta_{jt}^{na,c}\}$ the direction of the $\hat{c}_{1j}^{na} > 0$ suggests to increase α_{jt}^{na} with no change in β_{jt}^{na}. In this way, all the other rules can be easily interpreted and they are all summarized for all persona types and for buyer and sellers in the table below.

Table 3-13: Bidding Strategies

Rule	IF	THEN
1	$\hat{c}_{1i}^{a} > 0$ & $\hat{c}_{2i}^{a} > 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}\}$
2	$\hat{c}_{1i}^{a} = 0$ & $\hat{c}_{2i}^{a} > 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c}, \beta_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}\}$
3	$\hat{c}_{1i}^{a} > 0$ & $\hat{c}_{2i}^{a} = 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c}\}$
4	$\hat{c}_{1i}^{a} = 0$ & $\hat{c}_{2i}^{a} < 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c}, \beta_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}\}$
5	$\hat{c}_{1i}^{a} < 0$ & $\hat{c}_{2i}^{a} = 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c}\}$
6	$\hat{c}_{1i}^{a} = 0$ & $\hat{c}_{2i}^{a} = 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c}, \beta_{it}^{a,c}\}$
7	$\hat{c}_{1i}^{a} < 0$ & $\hat{c}_{2i}^{a} < 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}\}$
8	$\hat{c}_{1i}^{a} < 0$ & $\hat{c}_{2i}^{a} > 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}\}$

9	$\hat{c}_{1i}^{a} > 0$ & $\hat{c}_{2i}^{a} < 0$	$(\alpha_{it}^{a}, \beta_{it}^{a}) = \{\alpha_{it}^{a,c} + \frac{1}{2}\lambda_{i}^{a}, \beta_{it}^{a,c} - \frac{1}{2}\lambda_{i}^{a}\}$
10	$\hat{c}_{1i}^{na} > 0$ & $\hat{c}_{2i}^{na} > 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}\}$
11	$\hat{c}_{1i}^{na} = 0$ & $\hat{c}_{2i}^{na} > 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c}, \beta_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}\}$
12	$\hat{c}_{1i}^{na} > 0$ & $\hat{c}_{2i}^{na} = 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c}\}$
13	$\hat{c}_{1i}^{na} = 0$ & $\hat{c}_{2i}^{na} < 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c}, \beta_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}\}$
14	$\hat{c}_{1i}^{na} < 0$ & $\hat{c}_{2i}^{na} = 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c}\}$
15	$\hat{c}_{1i}^{na} = 0$ & $\hat{c}_{2i}^{na} = 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c}, \beta_{it}^{na,c}\}$
16	$\hat{c}_{1i}^{na} < 0$ & $\hat{c}_{2i}^{na} < 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}\}$
17	$\hat{c}_{1i}^{na} < 0$ & $\hat{c}_{2i}^{na} > 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}\}$
18	$\hat{c}_{1i}^{na} > 0$ & $\hat{c}_{2i}^{na} < 0$	$(\alpha_{it}^{na}, \beta_{it}^{na}) = \{\alpha_{it}^{na,c} + \frac{1}{2}\lambda_{i}^{na}, \beta_{it}^{na,c} - \frac{1}{2}\lambda_{i}^{na}\}$
19	$\hat{c}_{1j}^{a} > 0$ & $\hat{c}_{2j}^{a} > 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}\}$
20	$\hat{c}_{1j}^{a} = 0$ & $\hat{c}_{2j}^{a} > 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c}, \beta_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}\}$
21	$\hat{c}_{1j}^{a} > 0$ & $\hat{c}_{2j}^{a} = 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c}\}$
22	$\hat{c}_{1j}^{a} = 0$ & $\hat{c}_{2j}^{a} < 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c}, \beta_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}\}$
23	$\hat{c}_{1j}^{a} < 0$ & $\hat{c}_{2j}^{a} = 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c}\}$
24	$\hat{c}_{1j}^{a} = 0$ & $\hat{c}_{2j}^{a} = 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c}, \beta_{jt}^{a,c}\}$
25	$\hat{c}_{1j}^{a} < 0$ & $\hat{c}_{2j}^{a} < 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}\}$
26	$\hat{c}_{1j}^{a} < 0$ & $\hat{c}_{2j}^{a} > 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}\}$
27	$\hat{c}_{1j}^{a} > 0$ & $\hat{c}_{2j}^{a} < 0$	$(\alpha_{jt}^{a}, \beta_{jt}^{a}) = \{\alpha_{jt}^{a,c} + \frac{1}{2}\lambda_{j}^{a}, \beta_{jt}^{a,c} - \frac{1}{2}\lambda_{j}^{a}\}$
28	$\hat{c}_{1j}^{na} > 0$ & $\hat{c}_{2j}^{na} > 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} + \frac{1}{2}\lambda_{j}^{na}, \beta_{jt}^{na,c} + \frac{1}{2}\lambda_{j}^{na}\}$
29	$\hat{c}_{1j}^{na} = 0$ & $\hat{c}_{2j}^{na} > 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c}, \beta_{jt}^{na,c} + \frac{1}{2}\lambda_{j}^{na}\}$
30	$\hat{c}_{1j}^{na} > 0$ & $\hat{c}_{2j}^{na} = 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} + \frac{1}{2}\lambda_{j}^{na}, \beta_{jt}^{na,c}\}$
31	$\hat{c}_{1j}^{na} = 0$ & $\hat{c}_{2j}^{na} < 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c}, \beta_{jt}^{na,c} - \frac{1}{2}\lambda_{j}^{na}\}$
32	$\hat{c}_{1j}^{na} < 0$ & $\hat{c}_{2j}^{na} = 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} - \frac{1}{2}\lambda_{j}^{na}, \beta_{jt}^{na,c}\}$

33	$\hat{c}_{1j}^{na} = 0$ & $\hat{c}_{2j}^{na} = 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{a}) = \{\alpha_{jt}^{na,c}, \beta_{jt}^{na,c}\}$
34	$\hat{c}_{1j}^{na} < 0$ & $\hat{c}_{2j}^{na} < 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na}, \beta_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na}\}$
35	$\hat{c}_{1j}^{na} < 0$ & $\hat{c}_{2j}^{na} > 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na}, \beta_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na}\}$
36	$\hat{c}_{1j}^{na} > 0$ & $\hat{c}_{2j}^{na} < 0$	$(\alpha_{jt}^{na}, \beta_{jt}^{na}) = \{\alpha_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na}, \beta_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na}\}$

where

$$\lambda_i^a = \min\{\alpha_{it}^{a,U} - \alpha_{it}^{a,c}, \alpha_{it}^{a,L} - \alpha_{it}^{a,c}, \beta_{it}^{a,U} - \beta_{it}^{a,c}, \beta_{it}^{a,L} - \beta_{it}^{a,c}\}$$

$$\lambda_i^{na} = \min\{\alpha_{it}^{na,U} - \alpha_{it}^{na,c}, \alpha_{it}^{na,L} - \alpha_{it}^{na,c}, \beta_{it}^{na,U} - \beta_{it}^{na,c}, \beta_{it}^{na,L} - \beta_{it}^{na,c}\}$$

$$\lambda_j^a = \min\{\alpha_{jt}^{a,U} - \alpha_{jt}^{a,c}, \alpha_{jt}^{a,L} - \alpha_{jt}^{a,c}, \beta_{jt}^{a,U} - \beta_{jt}^{a,c}, \beta_{jt}^{a,L} - \beta_{jt}^{a,c}\}$$

$$\lambda_j^{na} = \min\{\alpha_{jt}^{na,U} - \alpha_{jt}^{na,c}, \alpha_{jt}^{na,L} - \alpha_{jt}^{na,c}, \beta_{jt}^{na,U} - \beta_{jt}^{na,c}, \beta_{jt}^{na,L} - \beta_{jt}^{na,c}\}$$

The λ variable, which takes the value of the minimum distance from the upper and lower bound values, attempts to limit the search space for beta to smaller bidding ranges in subsequent rounds, as long as the agent can win the trade.

Step A.3.4: Determine the new strategy variables from Step A.3.3, and re-compute for each hour:

Table 3-14: Bid Prices and Quantities

A	$(p_{it}^{a(*)}, q_{it}^{a(*)})$	using	$(\alpha_{it}^{a}, \beta_{it}^{a})$
B	$(p_{it}^{na(*)}, q_{it}^{na(*)})$	using	$(\alpha_{it}^{na}, \beta_{it}^{na})$
C	$(p_{jt}^{a(*)}, q_{jt}^{a(*)})$	using	$(\alpha_{jt}^{a}, \beta_{jt}^{a})$
D	$(p_{jt}^{na(*)}, q_{jt}^{na(*)})$	using	$(\alpha_{jt}^{na}, \beta_{jt}^{na})$

From
Table 3-14, re-submit **A-D** bids to the market. If t=T then stop, otherwise go to Step A.3.5.

Step A.3.5: Set t=t+1 and determine if the agent makes a profit, if so, go to Step A.3.6, if not, go to Step A.3.1.

Step A.3.6: Update the bidding variables as the current ones under the winning scenario. Reset the upper and lower bounds according to Update Strategy Variables process discussed below in Section 5C.

3.4.2 Section 5B: Market Clearing

Up to this point Section 5A has discussed the estimation methods for agent's price predictions and how these prices are adjusted in the simulation rounds by agents. We also discussed how the learning process helps agents to adjust their prices based on the values of the strategy coefficients. These coefficients help to determine which trading strategy to use. This section describes how the bids are cleared in the market clearing process. This process clears the all agents' bids to form a market-clearing price for every hour. The matching process is shown in the figure below.

The Market Clearing Process

- **Objective**: Clear all the buyer and seller agent bids to form a market clearing price and quantity for every hour
- **Roles**: Market clearing agent
- **Input**: Agents' bids: $(p_{jt}^{a(*)}, q_{jt}^{a(*)}),\ \ (p_{it}^{a(*)}, q_{it}^{a(*)}), (p_{jt}^{na(*)}, q_{jt}^{na(*)}),\ (p_{it}^{na(*)}, q_{it}^{na(*)})$ pairs for every hour: *t=1,...,24*
- **Output**: Market cleared prices (P_t, Q_t) for every hour *t=1,...,24*
- **Detailed Description**:

The market-clearing agent is an important component of the market. Its main role is to gather all offers and bids from all participants, then execute a matching algorithm (shown in **Error! eference source not found.**) to match buyers with sellers to a point where the market-clearing price is set for every hour. This market-clearing price for each hour will be used to settle the trades in the real-time market. The settlement process determines which agents win and which ones lose a trade. All other bids and offers that cannot find a buyer or a seller are not accepted in the market. Not having a trade accepted means there is no potential for profit for the agent. Therefore, agents are motivated to ensure their bids and offers are accepted in the market. Ensuring a trade is cleared in the market means asking a price that is likely to attract buyers, and vice versa. The cleared bids and offers by buyers and sellers can be classified as sealed Dutch and English auction types, respectively. Specifically, the supply side bids start low and continue higher (English); and the demand side bids start high and continue lower (Dutch) [Sueyoshi 2005]. Let the price $\boldsymbol{P^{DA}}$ and quantity $\boldsymbol{Q^{DA}}$ be the market clearing price and quantity pair. Since the market clearing agent's role is to satisfy buyer's demand with available supply, it will distribute the quantity based on a specific matching algorithm. Specifically, all supply offers are sorted in ascending order by $\boldsymbol{p_{it}^{*}}$; all buyer bids are sorted in a descending order by $\boldsymbol{p_{jt}^{*}}$. Based on the above matching algorithm, it is the goal to find sellers for every buyer, and buyers for every seller up to a point where an equilibrium is reached between demand and supply. The choice of being a buyer or seller will have direct impacts on profits, which will be determined by the settlement process, discussed next.

3.4.3 Section 5C: Settle Trades

Settlement Process

The importance of this process shows how we determine which agents win a trade and which ones do not. Recall that previous day cleared prices settle against the historical average real-time prices.

- **Objective**: To determine for each agent, that has their bid accepted or cleared, whether it won or lost the trade using historical average real-time prices as the settlement price.
- **Roles**: System
- **Input**: Agents' trades, historical average real-time prices for each hour.
- **Output**: Win or lose status for a trade for each agent.
- **Detailed Description**:

Since we are simulating how a market may evolve tomorrow, we do not have information on tomorrow's actual real-time prices. Therefore, we estimate these prices by taking the average of similar days of historical[10] real-time prices, as explained below, for buyers and sellers. Specifically, if tomorrow is a Sunday, we simply get all the historical real-time prices for Sunday as described in Steps C.1.1-C.1.4 below. We do not need any forecast data here because forecasts have already been used in the estimation process and not required in the settlement process to determine if traders make a profit or loss from their trades. The reason we look at similar days is because of the variation of the market day to day. Specifically, electricity

[10] As mentioned, we currently have 12 months of historical data.

consumption is different on weekdays than it is on weekends. One of the reasons being is because businesses are consuming more electricity in the weekdays as people go to work, and not so much in the weekends. Within weekdays the pattern of electricity consumption also varies and is not the same from day to day[11].

Step C.1.1: Let *K* represent the number of the day for tomorrow: where *K*=0 is Sunday, *K*=1 is Monday, *K*=2 is Tuesday, and so on.

Step C.1.2: Get all historical days (*d*) where the day is equal to *K*. Let

$$D^K = \{d_m |\ d = K, m \in \mathbf{N}\}$$

Step C.1.3: Let RT_t^K be the average real-time price curve for *K* for each hour *t*=1-24 where

$$RT_t^K = \{average\ of\ D^K\ for\ every\ t \in d_m\}$$

Therefore, RT_t^K contains average real-time prices for *K* for each hour *t*.

Step C.1.4: Settle the trades. As an example, consider an aggressive seller *i*'s cleared bid[12], for each hour *t* let profits be

$$\Pi_{it}^a = (P_{it}^{DA} - RT_t^K) * Q_{it}^{DA}\ ,$$

For a buyer multiply profits by -1. The reward variable for each agent for each hour is

$$agentwon_{it}\ = \begin{cases} 1, & if\ \Pi_{it}^a > 0 \\ 0, & if\ \Pi_{it}^a \leq 0 \end{cases}$$

If the agent won the trade ($agentwon_{it} = 1$), the strategy variables are updated because the β_{it}^a value resulted in a winning trade, similarly for other agents. The updating process is described below.

Updating Strategy Variables

Table 6-11 (in Appendix F) shows how the strategy variables can be updated in step A.3.6 above. If the agent won the trade from the previous round the same variables are used for the next round. In this way, the winning variables continue to be used based on the values of the

[11] Knowledge based on author's internal discussions with electricity traders.
[12] We would have to do this for all agent types.

coefficients: c_1 and c_2. If the agent did not win the trade, the strategy variables do not update at all and we re-estimate the profit equations and re-compute α and β for the next simulation round.

Up to now, Section 5A-5C represent step 5 in the T-Evolve* process. The core aspects are the forecast beliefs, agents' personas, and the learning process that helps to determine the probability of reward for a trade by estimating the profit equations. The strategy coefficients are then used to determine the bidding strategies for the agents. By accumulating knowledge about β, agents are able to adjust the choice of β in a more systematic way that takes into account both their forecast beliefs and personas. If a value of β is resulting in winning trades, agents continue to hold on to this value for subsequent rounds otherwise it is re-computed based on the values of the strategy coefficients. It will be shown in the case studies that both forecast beliefs and personas have significant impacts on agents' profits and in fact lead to very different trading strategies. The analysis process, step 6, is discussed next.

3.4.4 Section 6: Trace Data Analysis

- **Objective**: To present the results from the analysis of trace data to the user.
- **Roles**: User/System
- **Input**: Trace data table: TRAMAS_BID_DECISIONS (see 0 for a schema)
- **Output**: Market variable outcomes: profits, probability of rewards, trades by agent type, hour and position.
- **Detailed Description**:

The main form of analysis is through SQL queries of trace data that are specific to the information needs of the user; these queries are shown in Tables 2-7 in the PDF[13]:

1) Table 2: SQL Query for Trace Data
    a. Description: This query gets the agents' trace data for analysis.
2) Table 3: SQL Query Actual Profits
    a. Description: This query gets the profits by position using the forecast dates for real-time prices. Specifically, it shows that had the trader used the cleared prices generated by TRAMAS, what the profits would be in tomorrow's market.

[13] http://people.ucalgary.ca/~smaurice/PhD Research-SQL Queries.pdf

3) Table 4: SQL Query for Simulated Profits
    a. Description: This query gets the profits by position using average historical real-time prices. Specifically, it shows that had the trader used the cleared prices generated by TRAMAS, what the profits would have been as compared to the average real-time prices.
4) Table 5: SQL Query for Bidding Strategy
    a. Description: This query shows the bidding strategies by agents for each hour based on the values of c1 and c2.
5) Table 6: Best Trades
    a. Description: This query shows the best trades based on their probability of rewards by position.
6) Table 7: Query for Average Alpha and Beta Values
    a. Description: These queries get the average values for the strategy variables: beta and alpha, for each agent, position and hour.

The results of the queries are further analysed in Microsoft EXCEL[14] and will be extensively discussed in case study #2.

3.5 Summary

This chapter has provided a comprehensive summary of the methodology underlying TRAMAS. The main simulation steps were discussed in sections 5A-6. The agents' bidding strategies incorporate both personas and forecast beliefs. The bidding strategies are chosen from strategy coefficients generated from profit equations' regression models that systematically determine the probability of reward of trades and factors in to what price and quantity an agent bids into the market. Using a β variable as the markup or discount factor on prices, an agent can aggressively or non-aggressively generate bid prices. A market-clearing agent using a matching algorithm then clears the prices from all agents. Profits and losses are generated from cleared trades, and profits generated from specific choices of β are used as learned behaviour for subsequent simulation rounds. The analysis component of TRAMAS generates insights that are extracted

[14] Naviage to my research page for the analysis: http://people.ucalgary.ca/~smaurice/phddata_research_analysis.xlsx.

from trace data through SQL queries that meet the specific information needs of the user. Before discussing the case studies we next discuss the architecture of TRAMAS.

CHAPTER 4: TRAMAS Architecture

4.1 Overview

Up to this point of the thesis we have discussed what the challenges are in providing decision support to traders. These challenges center around changing market conditions together with differences in participants' personas and forecast beliefs that all have an impact on future market prices. Steps 1-8 help to address these challenges in an evolutionary context coupled with an analysis component that will help traders determine the opportunities and risks in tomorrow's market. This section discusses TRAMAS at the application and conceptual levels.

4.2 Challenges in Building an Effective Support Environment

One of the key challenges in this thesis was to turn the concept of a trading simulator into reality, which we accomplished. It was also one of the key personal successes for the author. The integration of different technologies as well as concepts was by far the biggest challenge. As shown below, the implementation of the TRAMAS application involved several different programming languages:

(1) C++
(2) SQL
(3) PHP
(4) Javascript
(5) MATLAB script

With different technologies:

(6) MATLAB
(7) Microsoft SQL 2005: functions and stored procedures
(8) Borland C++
(9) Microsoft IIS 7 manager
(10)Hypertext transfer protocol (HTTP)

The collection, processing and analysis of the data were also a challenge. Ensuring the process of data collection remained continuous, without any server downtime, required close monitoring of the servers by the author. It is hoped that in the future this manual monitoring can be automated to a greater extent while minimizing human intervention.

4.3 TRAMAS Design Approach

A common framework to describing modeling and simulation highlights three primary artefacts: source system, model and simulator [Singh et al., 2003]. The source system is real or virtual and is intended to be modeled by the simulation. The model is any physical, mathematical, or logical representation of a system, entity, phenomenon, or process [ibid.], and a simulator is any computational system (such as a single processor, or a network of processors) that can execute a model to generate its explicit and implicit behaviour [ibid.]. The system employs an experimental framework to help validate the inputs and outputs from the simulation. Specifically, an experimental frame specifies the conditions under which the system (and/or its model) is experimented with, in the hopes of attaining some data under well-defined and observable conditions [ibid.]. There also exists a relationship between the model and the simulator, which are seen to be appropriate representations of their system specifications that can be used for model and simulation validation [ibid.].

There have been several methodologies and practices proposed within the software engineering area that provide guidance in software design. While there is no one way to design software, these methodologies and practices are mature and widely accepted in software engineering [Bass 1998; Booch 1994; Booch 1998]. The model-view-controller (MVS) architectural style aids in creating a blueprint for applications and is widely used for its simplicity and applicability for software systems that are interactive in nature [Singh et al., 2003; Java Blueprints, 2003].

TRAMAS is a modeling and simulation technology that enables the modeling of markets made up of specific market components that are used in the simulation and later analysed using the analysis component. The fusion between system theoretic concepts and the MVC approach are at the core of the TRAMAS design. At the highest level of abstraction, the TRAMAS application is a market model simulator that simulates buying, selling and clearing of prices for some good or commodity of value. From an intelligent decision support perspective TRAMAS is an interactive tool for decision making that incorporates machine learning (discussed above in the learning process) for well-structured decisions and planning situations as well as specific estimation methods used by agents and integrates information systems for decision support (see [Gottinger et al. 1992] for a deeper discussion on IDSS). The intelligence aspect comes from the learning process that uses the profit equations to determine the bidding strategy that has the highest probability of reward. How the MVC are connected is discussed next.

4.4 TRAMAS Software Architecture

Following from the MVC paradigm described above, the software architecture of TRAMAS is shown in Figure 4-1 below.

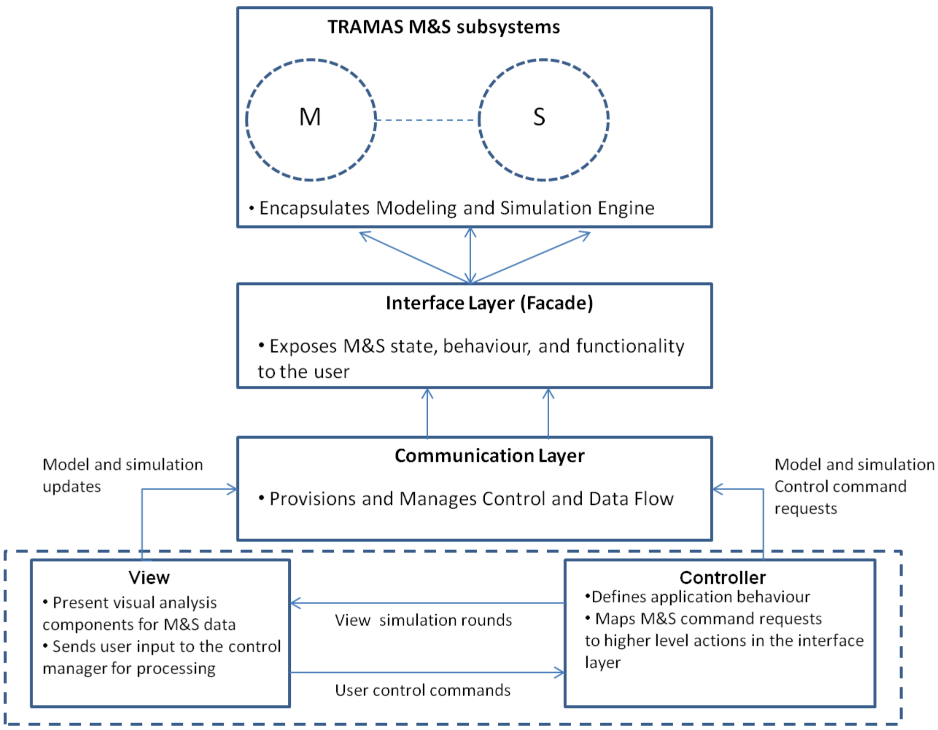


Figure 4-1: TRAMAS Software Architecture

The model contains the core modeling and simulation logic for TRAMAS; the external static and dynamic properties that are exposed by the model are important for the interaction between the controller and the view [Singh et al., 2003]. The connections with the MVC parts are facilitated by the interface and communication. The interface handles the behavioral and structural aspects of the model that are made available to the view and controller. From a software perspective, the model is instantiated with classes that have user specified design level and domain level relation to the modeling and simulation. After a model is instantiated it can be executed in the simulator class by having access to execute the {start simulation} and {stop simulation} methods. The communication level works in conjunction with the interface level which when established for an instance of a model handles the communication issues such as coordination between agents bidding behavior, timing of clearing bids by matching a buyer to a seller, data formats, etc. The communication layer sits between the interface layer and the view and controller to address these issues. The interface layer plays a critical role because it handles the complexities of the model and is the only layer that can access the inner data elements of the model. While the interface layer does not add any functionality to the model it is a visualization of the inner elements of the model, specifically it presents two abstract views of the model: abstract modeling and simulation sets. These abstractions offer the necessary syntactic and semantic software structures while not imposing any particular structure on the model. The following list is provided by the abstract modeling and simulation sets.

4.4.1 Abstract Modeling Set

- Class structure for models that are well defined based on user scenarios
- Access to static model information (e.g., data, forecast beliefs, agents personas, simulation id, number of agents, hours of operation for special agents, estimation methods used by agents, analysis of results, etc.).
- Access to dynamic model information (e.g., simulation rounds, cleared prices, cleared volumes, bidding strategies).
- Well-defined set of data-types used by the simulation models (e.g., numbers, strings, etc.).

4.4.2 Abstract Simulation Set

- An explicit, well-defined set of simulation behaviors (e.g., stop, start, enter parameters, customize agents, and view simulation results).
- Access to general simulation information (e.g., simulation round, output values, agents types, number of agents chosen, estimation method used, forecast shapes, etc.).
- Listing and access to all previous simulation models.[15]

[15] This is a future enhancement.

4.4.3 View

The view allows the user to interact with the system through a graphical user interface (GUI). It also acts as a gateway between the end user and application functionality. From a user perspective, the view allows for inspection of the simulation execution results enabling the user to stop the simulation and analyse its results at any time during the simulation. The visual representation of the simulation results are abstractions of the structural and behavioural aspects defined in the interface layer. Another important aspect of the view is to facilitate experimentation with models. Allowing users the flexibility in modeling markets and viewing the simulation results of each model and later analysing the trace data[16]can serve to distinguish between models' results as part of the T-Evolve* process steps 6-8. Storing simulation results in the table[17] allows the user to compare models results based on specific criteria. Some issues could occur in the representation of the data pushed down from the model. Specifically, it is critical to maintain logical correctness, such as synchronizing the current state of the model with its visual representation [Singh et al., 2003]. The implication of this is that it may nullify model validation [ibid]. Thus, maintaining synchronicity between data that is actually in the model with the view should be given serious concern. Logical correctness can be maintained and should be addressed, ensuring that the view, controller and communication layers are synchronized as appropriate.

4.4.4 Controller

The controller controls both the application level logic and the model level logic. The application level logic resides in the view and controller, and the model level logic resides in the model. Within TRAMAS, the application logic deals with data visualization, initialization of the session, termination of the session, etc. The model level governs the creation of market models with the user chosen parameters, starting and stopping the simulation, etc. If the user terminates the TRAMAS session, this control gesture is triggered in the view by the user and mapped to a specific event in the controller for execution. In TRAMAS, if an event is not mapped in the controller then it is mapped to an appropriate method in the communication layer and sent to the user at the interface level.

---

[16] Currently this is a manual process using pre-defined SQL queries [see my research website for these queries: http://people.ucalgary.ca/~smaurice/PhD%20Research-SQL%20Queries.pdf

[17] Results are stored in the TRAMAS_BID_DECISIONS table in Appendix C.

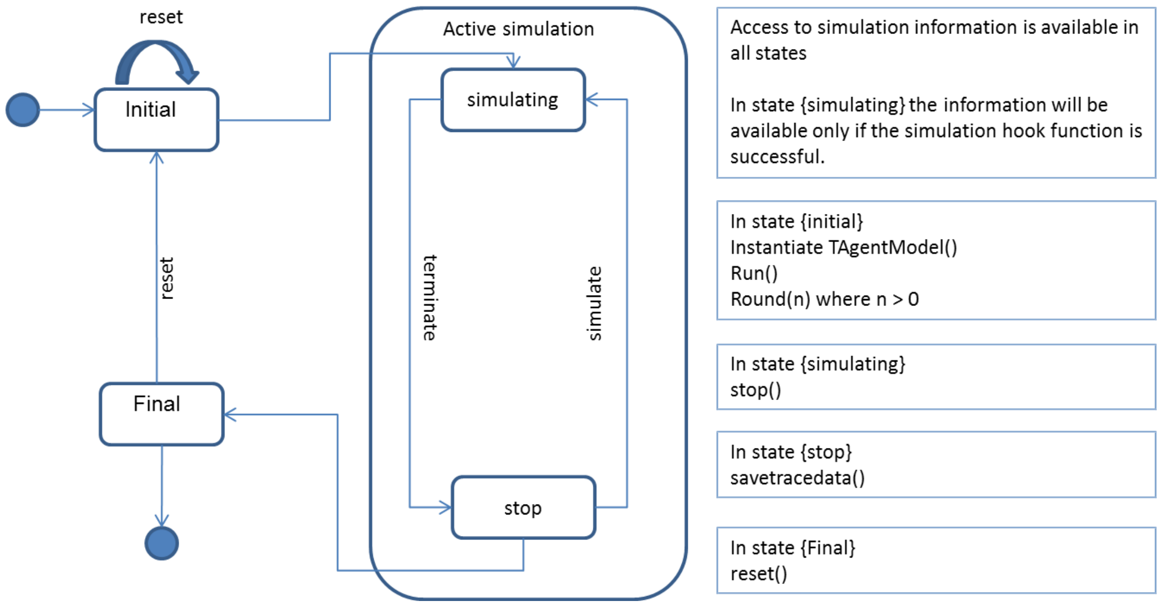


Figure 4-2: Dynamics of the Simulation

4.4.5 Simulation Dynamics

The dynamics of the simulation can now be described. In Figure 4-2, the instantiation of the TAgentModel is initiated at the start of the simulation. In the simulating state all information is available only if the simulation hook function is successful. Once in a stop state, the data collected from the agents' actions are saved in the database[18] for analysis. The connection between the interface layer and the controller makes it possible to view the simulation results.

Figure 4-3 shows a sequence diagram depicting the interactions between the model, view and controller from user initiated commands. User commands generated within the simulation environment are sent to the view that generates user command events that are sent to the controller for processing at the model level. At the application level, commands are within the controller itself. The controller has logic built in to execute user commands, which acts as a proxy for the model.

[18] In the TRAMAS_BID_DECISIONS table.

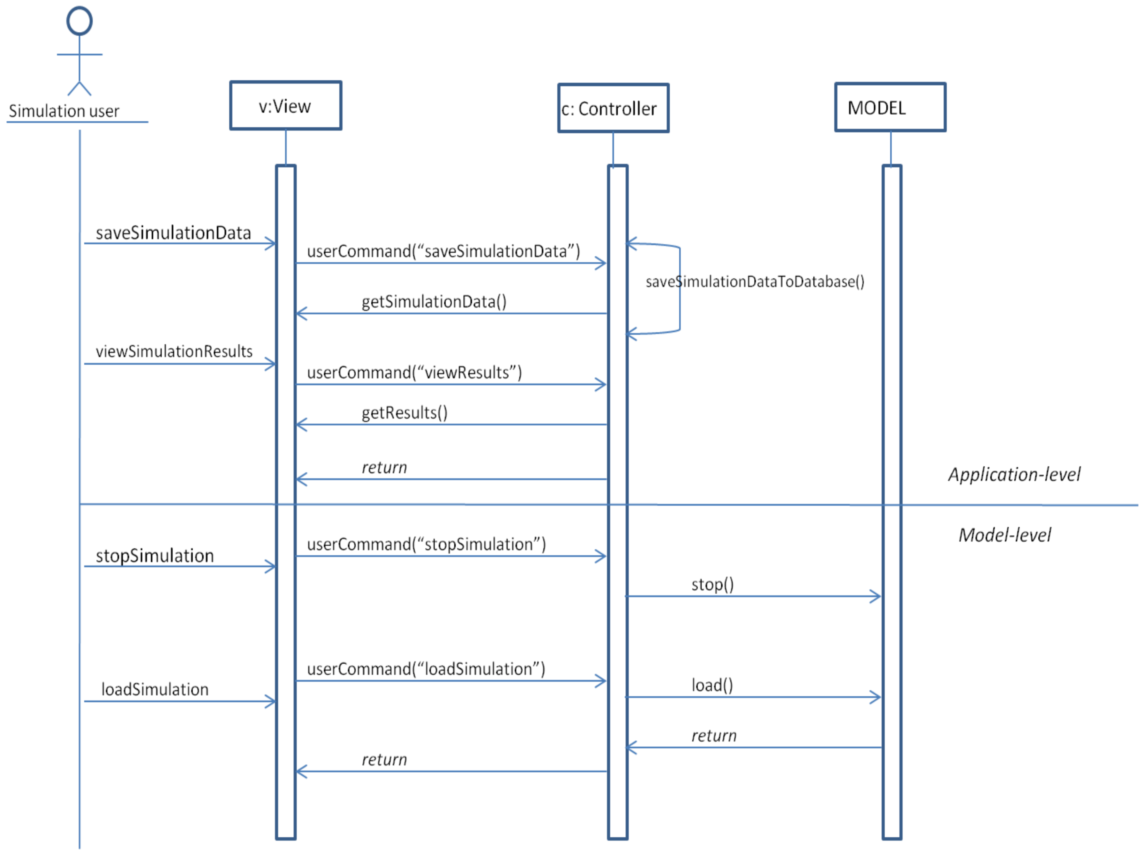


Figure 4-3: TRAMAS Sequence Diagram

4.5 Internal Agent Model

In TRAMAS, agents derive their beliefs from the information in their environment; beliefs will vary between agents based on the types of personas they have. For an aggressive agent, the beliefs and objectives will be much different than from an agent that is non-aggressive. The internal model for the agent, shown in Figure 4-4, consists of:

- External influences: these influences such as extreme weather conditions are likely to be embedded in the forecast data, whether these influences will materialize is a belief a user can modify in the agent's forecast belief.
- Perceptions about its environments such as who is likely to be in the market.
- Persona, which will be used to adjust the beliefs.
- The beliefs agents have about the information they process or given to them. This impacts the trading strategies they choose.

- Objective on *what to do*, and a plan on *how to do it.* The agents bid prices into the market in the hopes that their bid will be accepted and cleared. The price bids are determined by the β variable, which is computed using a particular trading strategy.
- Action to take in terms of bids; here the agent can use any one of the following such as regression modelling, or neural networks.

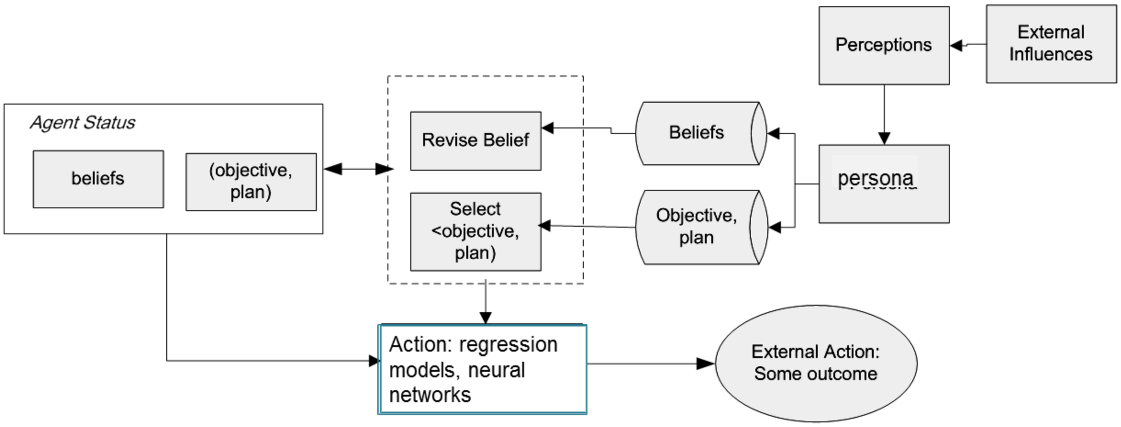


Figure 4-4: Agents' Internal Model: Buyer and Seller

4.5.1Agent Assumptions

The following assumptions are important in the simulation.

a) Agents do not know whom they are trading with or how the other agents internal decision making functions.
b) Agents only have knowledge about the information about themselves.
c) The information they have about them is influential on their decision making.

The agent-bidding model discussed next shows how agents use their perceptions to execute bidding actions.

4.6 TRAMAS Bidding Model

Figure 4-5 shows the bidding goal, tasks and user application. The bid goal to be achieved is based on the private and public data available for the agents. The bidding task waits for the private and public data to become available before generating the bid action. The private data for each agent are the forecast beliefs (α), prices mark-up or mark-down (β), the transactions it made (price and quantity), knowledge base, its profit and loss, and reward probability. The public data are the cleared market prices, and forecast data. The bidding decision uses the persona and forecast beliefs chosen by the user to satisfy the goal of the bid; the bidding task modifies the internal parameters (i.e. this could hold parameters used in the price forecasts).

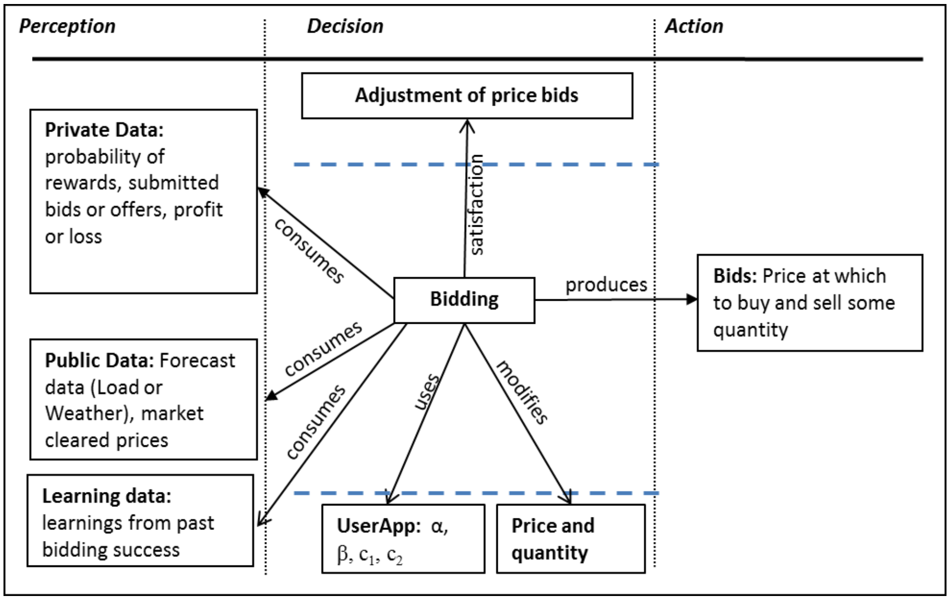


Figure 4-5: TRAMAS bidding goal, task and user application

At a conceptual level, the simulation is defined next.

4.7 Defining the Simulation

What we are simulating is a market model chosen by the user, to provide support for given decisions by exploring a PMO. TRAMAS facilitates an agent-based simulation of this market model:

Simulation Goal**:** The general goal is to observe the behaviour of the application when agents interact to create a market cleared price for each simulation round. Our application allows users to:

1. Observe emergent behaviour as a result of agents buying and selling actions in the environment
2. Capture agents' trace data for analysis

Simulation Inputs:

At the beginning of the simulation:

1. User assigns actors to personas which are instantiated by agents, or assigns actors to agents directly:

   a. Persona is how an actor wishes to represent himself to others under a particular market model. The beliefs can be a part of the agent's persona.

2. External data from different sources start the simulation
3. Establish forecast beliefs
4. Estimation method used by agents to initially predict prices
5. Specify whether an agent is a buyer or seller

During the Simulation:

1. Agents use their forecast beliefs, personas and environment to perform actions, such as submitting buy and sell bids in the market that are subsequently cleared by the market clearing agent for each simulation round.
2. Agents learn by using the values of β from previous rounds to determine the bidding strategy for the next round. If an agent made a profit from a trade in the previous round with a specific β value, then this value is used again in the subsequent round. Otherwise a new β is computed.
3. After all agents have submitted their bids, the market clearing agent clears all the bids.
4. Trace information is being captured in the trace database for future analysis.

Simulation Outputs

The expected outputs of the simulation are:

1. The market cleared prices.
2. Trace data to be analysed to determine a trade plan to help users make trading decisions.

Simulation of the market model is discussed next.

4.8 Market Models' Simulation

Figure 4-6 shows the actors in this market model as the buyers and sellers of an asset. The market clearing agent (market moderator) matches the buyers and sellers based on what the buyer is bidding, against what the seller is asking. Users can model a market by choosing market components, i.e. the forecast data and personas for actors in the market, that they think will offer insights into how the market may evolve tomorrow. Several actors in the market can have the same personas.

The internal parameters store information about models; agents use estimation methods to decide on actions. Agents in TRAMAS establish numerical beliefs about what to bid into the market by using predictive models such as neural networks or regression models. There are many other predictive models available and these can be implemented in TRAMAS in the future. Trace data are captured during every simulation round.

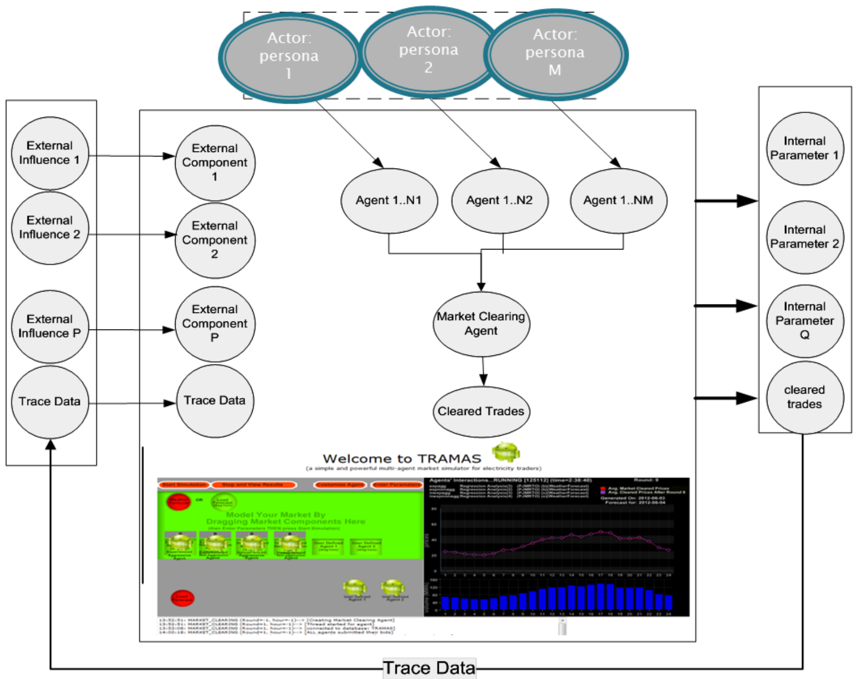


Figure 4-6: Market Model Simulation

We discussed above the conceptual model of TRAMAS. The intention is to [Kung et al., 1986]

1. Enhance our understanding of the representative system
    - Within the trading domain, buyers and sellers trade anonymously so it is not possible to see the individual, discuss the trade with him or determine what data and estimation methods they use to decide on what to trade. By using TRAMAS users are able to simulate what they believe the market may contain. Using the steps in the T-Evolve* process users can model, and explore a PMO and help to improve their understanding of tomorrows market by creating different iterations of the market model. TRAMAS cannot predict with certainty how the market will evolve tomorrow, it will help to analyse how tomorrows market may evolve in a more systematic way and also help to view tomorrows market from different

perspectives, which may not be possible from conventional modeling methods such a mathematical models.

2. Provide a means of sharing system information and extracting system specifications
    - We identified forecast beliefs and personas to be important in TRAMAS. There may be other factors that could help to improve our understanding of tomorrow's market. Specifically, TRAMAS focuses on the financial trading market, there could be factors of the physical market on which the financial market is based on, that may add additional value in understanding tomorrows market.
3. Document the system for future reference and use it as a means for collaboration.
    - Extensions to the system in the areas of different market components could give TRAMAS wider applicability.

The next section discusses the TRAMAS application.

4.9 TRAMAS Application

There are several ways a user can control the system; these can be classified as application level controls and simulation level controls. The application control includes starting the simulation, stopping the simulation, customizing an agent, and viewing results of the simulation using the analysis component. The simulation level controls enable the user to control the simulation itself. These include changing simulation parameters, and entering parameters for a new simulation. The application architecture is discussed below.

4.10 Architecture of the Support System

The proposed architecture of the TRAMAS support environment in Figure 4-7 shows the structure of the components that make up the architecture and the dataflow between the components.

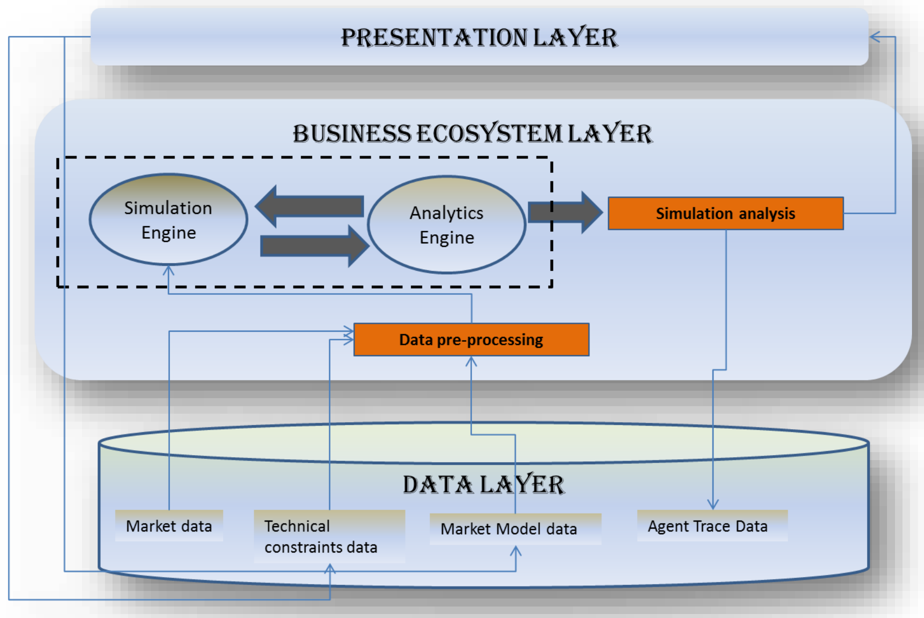


Figure 4-7 Support Environment

The support environment consists of the following:

1. *Presentation layer:* this layer houses the interface through which the user interacts with the system, it is made up of three parts. Part 1 is where users construct the market model that accepts two sets of inputs: market model using drag-drop functionality and parameters for agents; the results are presented to the users. Part 2 shows the results of the simulation in real-time. Part 3 is where the results of the analysis are shown. The presentation layer, Parts 1 and 2 are fully functional and developed as part of this research. We have yet to implement a user-friendly interface for Part 3.
2. *Business Ecosystem Layer:* this layer is the core of the support environment and implements and simulates the various market models and algorithms used by agents to make buy and sell decisions. It also does post-simulation analysis of the agents' trace data that is presented to the user.
3. *Data layer:* contains all the data needed for the support environment, which consists of market data, technical constraints, market models, and trace data.

4.11 Implementing the Different Components

The components of the application are shown below to give the reader a sense of the user environment and how the component pieces are implemented. The architecture allows for a flexible implementation that is agnostic to what actual components are. We will explain in more details below.

4.12 Data Layer

The market data are collected using a data scrape server that scrapes data from the PJM and Weather.com websites. This data is scraped on an hourly basis, which make up the core sets of data: load forecast and weather forecasts, that are required for the market models' simulations. The technical constraints data are the parameters chosen by the users for each of the agents. As shown in Figure 4-8 below, the user has the following choices:

- The market to analyze: PJMRTO (currently only option)
- Instances of agents
- Estimation Method
- Buyer or Seller
- Forecast Type: Weather or Load Forecast
- Forecast Belief

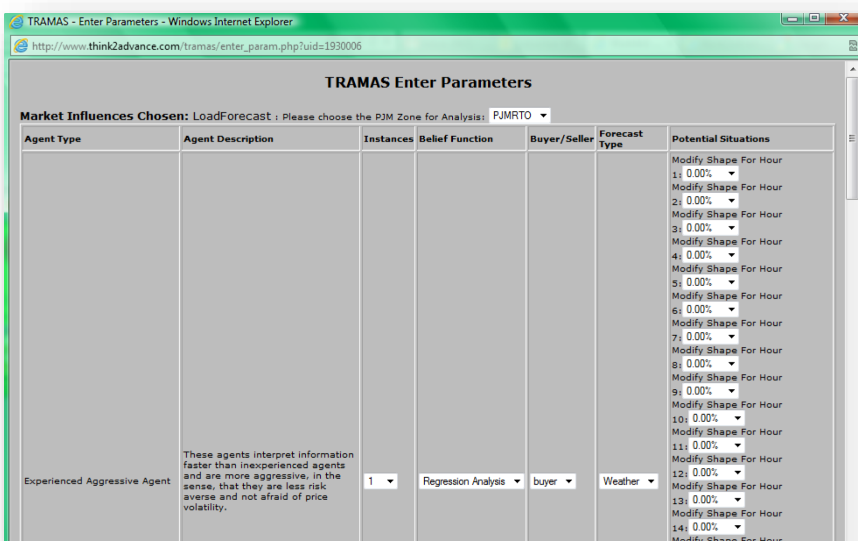


Figure 4-8: Agent Parameter Choices

The market model data is comprised of the components of the market model. This includes the forecast data type: Weather or Load, and the agents' types together with the above agent parameter choices. Lastly, the agent trace data records all of the agents' actions occurring in the simulation for later analysis.

4.13 Business Ecosystem Layer

The ecosystem captures all of the interactions occurring between the different components.

1. Data pre-processing: This component pre-processes the data and creates one denormalized table, shown below, that is used as input into the simulation engine. The implementation of this is done by a combination of C++ and SQL. The table has the following columns:

Table 4-1: Denormalized Table

Column	Description
Effective_date	date
Effective_hour	Hour: 1-24
Rtlmp	Real-time prices
Atemp	Temperature in Fahrenheit
Adalmp	Day-ahead prices
Aload	Load forecast
Agentid	Agents id
Simid	Simulation id
Round	Simulation round
Agenttype	persona
Cgroup	Group agent belongs in
Groupid	Group id

2. Simulation Engine: This component instantiates the agents in the market model, using the constraints and the market data to create a multi-threaded environment. Each agent has its own thread and acts independently of other agents. The buying, selling and clearing

of agent bids is all happening here. The implementation of the simulation engine is done using a combination of C++ and SQL.

3. Analytics engine: This component manages all the agents' requests. It executes the estimation method: regression and neural network models. It is also responsible for managing the learning aspect of each agent which determines the trading strategy the agent should use. The analytics engine is implemented using a combination of MATLAB and SQL.
4. Simulation analysis: This component analyzes the simulation results in real-time. It presents the results of the simulation rounds to the user. Each simulation round shows the market cleared prices for each hour. The simulation analysis is implemented using a combination of MATLAB and SQL.

4.14 Presentation Layer

The presentation layer is a core component that ties the business ecosystem layer and the data layers together. The presentation layer is implemented using Javascript and PHP. It is completely web-based. It is a friendly and intuitive design that puts little burden on the user for selection criteria and provides a rich and powerful environment to show how results are being generated and analysed consistent with the recommendations from [Power and Sharda 2007]. The green palette is where the user drags and drops the agents (androids) and forecast data (red balls) they want to use in their market model. The black palette shows the market cleared prices when the user starts the simulation. Figure 4-9 shows an actual simulation for 125112.

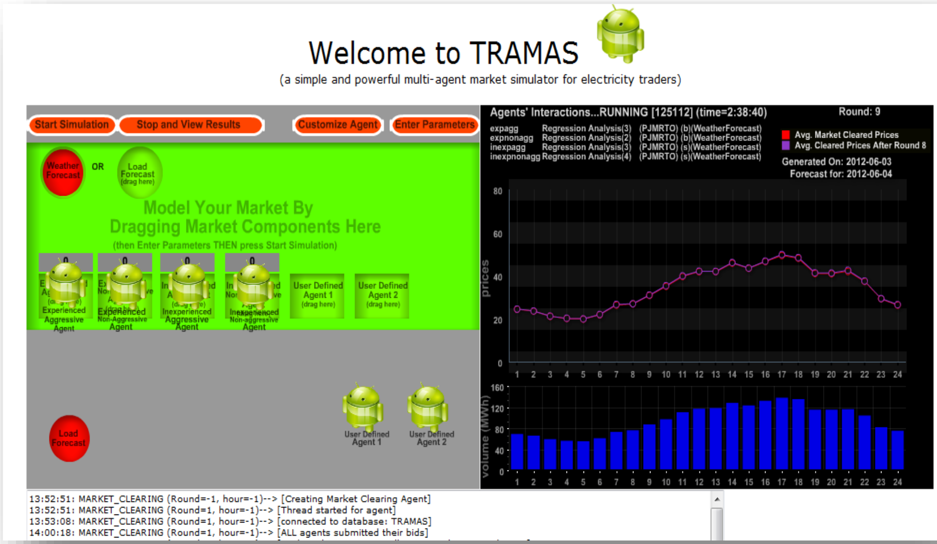


Figure 4-9: TRAMAS User Interface

The next section discusses the solution architecture.

4.15 TRAMAS: Solution Architecture

We can now discuss the complete solution architecture shown in Figure 4-10.

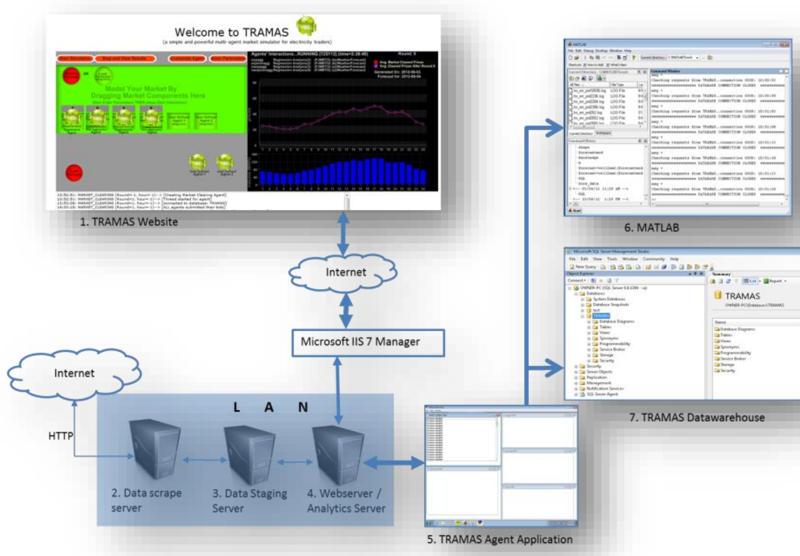


Figure 4-10: Solution Architecture

The components of the solution:

1) TRAMAS Website

a) This is where users choose their market model. Each component of the market model requires the user to drag and drop the components on the green palette. In Figure 4-11 users can customize an agent by modifying the agent's code:

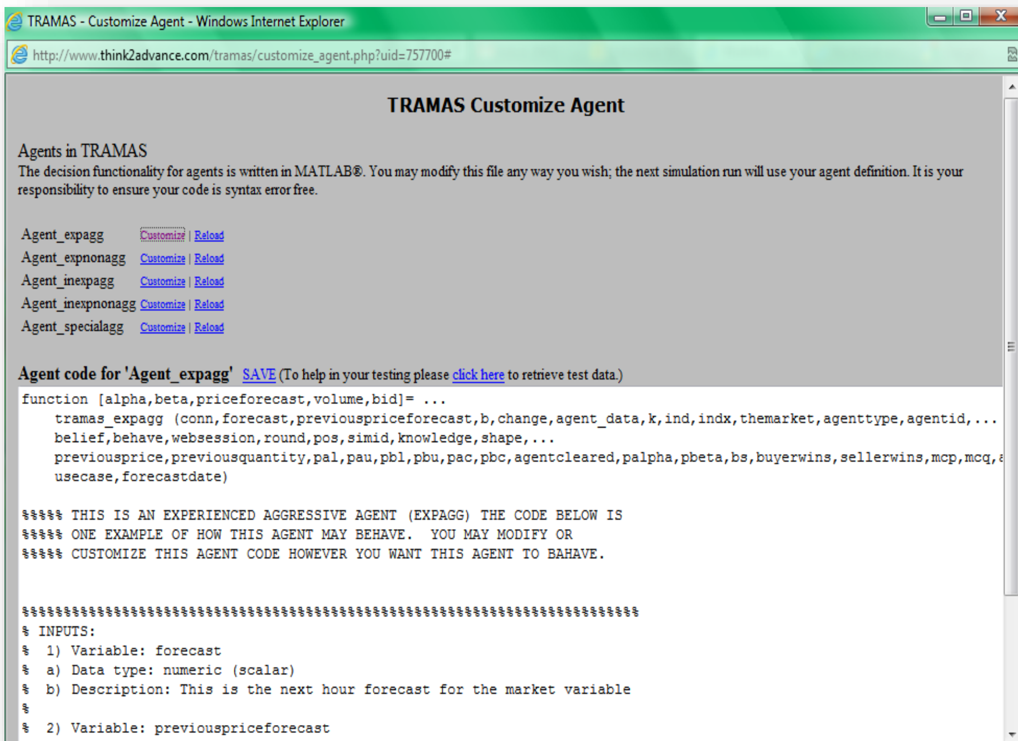


Figure 4-11: TRAMAS Customize Agent Window

Figure 4-10 also shows how the data is brought into the system for analysis. It contains:

Data Scrape Server

1. The data scrape server scrapes the PJM.com website for:
   a. Price data (real-time and day-ahead)
   b. Load Forecast data
2. Weather forecast data are scraped from Weather.com for the PJM area.
3. The scrape engine runs every hour using the HTTP protocol to connect to the website and automatically downloads the data.

4. Once downloaded, the data are moved to the data staging server.

Data Staging Server

1. This server runs an ETL procedure to store the scraped data into a SQL server called ZOOM2.

Webserver/ Analytics Server

- The webserver serves all the functionality required for the TRAMAS website to function. The web server software is Microsoft Internet Information Services Manager (IIS) 7. Once a connection is initiated from the user on the TRAMAS website by pressing the "START SIMULATION" button – it initiates the TRAMAS Agent Application.

4) TRAMAS Agent Application
    - This is the main application. It is written in Borland C++ using an object-oriented method. TRAMAS is a multi-threaded application where each thread has its own memory segment independent of other threads. Two additional applications are used for computing bidding prices:
        i. MATLAB
        ii. SQL Server Datawarehouse
5) MATLAB
    - This is the analytics engine for TRAMAS. The estimation methods: Regression analysis and Neural Network are computed using MATLAB.
6) TRAMAS Datawarehouse
    - This is a Microsoft SQL Server database and is the source of all data used in the simulation as well as the stored procedures:
        i) CLEARBID
            (1) Used by the market clearing agent to clear the agents bids
        ii) CLEAREACHHOUR
            (1) Calls Clearbid
        iii) SUBMITBID
            (1) Called by each agent when submitting bids

4.16 Summary

The current implementation of TRAMAS still requires research and further work in the areas of incorporating different personas, incorporating more data other than weather and load, and different estimation methods. The user interface for the analysis component still needs to be developed.

The MVC concept lends itself to defining the design constructs in TRAMAS. The synchronization between the model, view and controller are given serious concern as they are critical in the model validation and analysis stages.

The simulation was defined at the conceptual and application levels and showed what is being simulated, including how the interactions between the modeling constructs take place. The types of decisions that one can make also highlight the decision support aspects of TRAMAS for traders. The T-Evolve* process will become critical in helping users choose different market models as well as helping them to interpret the results so a final trade plan can be established. It is believed that the generality, and simplicity, of the design constructs make TRAMAS applicable to any type of trading domain.

The next chapter presents two case studies. Case study #2 applies these concepts and shows how TRAMAS is used to provide decision support for traders. However, before we get to this, case study #1 discusses the validation of TRAMAS by experts.

CHAPTER 5: EXPERIMENTAL EVALUATION AND VALIDATION

5.1 Overview

This chapter presents two case studies that follow the suggested guidelines in [Karlstrom & Runeson 2006; Runeson & Höst 2009; Robson 2002]. The first case study performs an analysis of the survey results from industry experts and answers research questions R1-R3. The second case study is an embedded case study where several units of analysis are studied in the same case [Runeson & Höst 2009]: in this case study we have four different units of analysis for the research questions R4-R6 and we validate the simulation output. Specifically, for R4 the unit of analysis are bidding strategies, for R5 they are profits, for R6 it is the experience level of agents and we validate the simulated prices from the PMOs. We use an embedded case study only because the context of the units of analysis come from the PMOs, and the research goal to analyse the effects of changes in forecast beliefs and personas on the cleared market prices is the same [Runeson & Höst 2009] but the goal cannot be achieved if the reader does not have confidence in the simulation results, hence output validation is also performed.

According to the recommendations by [Kitchenham et al., 2002] each case study contains three elements: background information, discussion of research hypotheses, and information about related research. The two former elements are discussed for each case study while the latter is presented in the related works chapter.

5.2 Case Study #1: Expert Validation (Research Question R1-R3)

5.2.1 Context

The goal of this case study is to investigate the usefulness of the TRAMAS application for industrial use. To investigate its usefulness, we present online survey results from a cross-section of industry experts at varying professional levels ranging from Director to Sr. Analyst at different trading companies across North America specializing in electricity trading in different markets. In total, nine (9) experts (out of 9) responded, between June 12, 2012 to July 31, 2012, to the survey: one (1) director, three (3) managers, and five (5) senior analysts from major utilities in North America with 1000 employees and greater. The level of experience required from the respondents had to be greater than five (5) years in the trading industry, special knowledge about electricity was not mandatory but was nice to have. There was no payment given to respondents to participate; participation in the survey was voluntary.

5.2.2 Assumptions and Constraints

The following are the assumptions and constraints that apply to this case study.

1. The online survey was available to respondents for 6 weeks
2. Nine experts were identified for this study
3. The respondents only evaluated the PMOs
4. The respondents were anonymous to each other
5. No training was provided to respondents and all information was available on the survey website
6. The survey website was developed by the author and it was secured by a username and password
7. The author did not interact with the respondents after the initial email inviting them to take the survey
8. All respondents were anonymous – in no way is it possible to connect answers to an individual's identity
9. Respondents voluntarily answered the online survey and no incentives including financial were given to the respondents
10. All respondents have more than five years of experience in the trading industry

What are the implication to the results if some of the assumptions are false? For 1, extending the survey beyond 6 weeks wouldn't have had much impact on the results as all of the nine respondents responded in this time. For 2, having only nine experts could influence the generalizability of the results. It could be that non-respondent bias may be present, in that the survey could have missed out on the opinions and feedback from a wider group of experts. Therefore, the possibility is there for the results to be influenced by more negative feedback. Having a wider range of experts could also be a direction for future research. For 3, having experts evaluate only the PMOs and not the building of the market models themselves in TRAMAS avoided the author spending time and effort training the experts on TRAMAS.

However, had the experts built and simulated the models themselves could have provided greater insights into the usefulness of the user interface and whether it was user friendly and intuitive to use. It could also have influenced the expert's responses in the questionnaire, especially question E7 below that asked if they would be confident in using TRAMAS to trade in the real market. If users had a negative experience using TRAMAS this could have resulted in more negative feedback from the experts. For 4, had the respondents not been anonymous this could have biased the results as some experts could have negatively or positively influenced each other and biased their true responses. For 5, no complaints were received from the respondents regarding the information on the survey website. For 6, securing the database was a requirement for ethics approval. For 7, had the author interacted with the respondents during the survey it could have biased the experts by potentially influencing their responses. The fact that there was no interaction with the experts is more likely to engender a more non-biased response from experts about TRAMAS. For 8, anonymity was a requirement for the ethics approval in order to ensure and respect the privacy of the experts. For 9, in no way were experts forced or coerced in answering the survey. The voluntary nature of the survey was a requirement for ethics approval but it also encouraged the experts to provide responses without being influenced in any way by the survey itself. For 10, having 5 years or more experience ensured that their understanding of the industry and other technology was as wide as possible. Had the respondents had less than 5 years could have limited their knowledge to some degree and would have provided a less critical response? Having more experience only meant that the experts would be more critical about TRAMAS and the value it brought to them.

5.2.3 Background

Industry experts were surveyed to validate the modeling constructs, and results from TRAMAS. This survey included the following:

1. Market model components such as:
    - Agent personas and market clearing agent
    - Data components: Load and Weather
    - Analysis of trace data for decision support
    - Machine learning
2. Behavioural components:

- Agent price and volume bidding behaviour
- Market cleared prices

3. Beliefs:
    - Forecast
    - Prices
4. Model Assumptions
5. TRAMAS process model
6. TRAMAS main model results
    - Actual market price versus model generated prices
    - Beta and alpha strategy variables
    - Agents bids and offers
    - Best trades
    - Prices submission per agent for each hour

The users were asked to choose among the following for each construct and results:

- Missing Most Information
- Contains Some Information
- Contains Key Information but with Gaps
- Contains Most Key Information
- Comprehensive Coverage
- N/A

The ethics application form, and the ethics board approval can be seen in Appendix A and Appendix B , respectively. The informed consent form was displayed to the users immediately as they log into the survey website.[19] The users were informed about how their privacy will be maintained and, among other details, that they can exit the survey at any time. The survey results were stored in a password protected Microsoft SQL database and users were able to view their results online using a username and password.

[19] The survey can be found here: http://www.think2advance.com/tramas/phd_start.php

5.2.4 Study Design

This case study is applied research that tries to understand if industry experts find TRAMAS to be an effective technology that could be used in the real world and answer the research questions R1-R3. The unit of analysis are industry experts' responses who have a broad knowledge in the area of energy trading.

5.2.5 Subjects

The subject sampling strategy was to choose experts based on the following criteria:

1. Professionally works in the energy trading industry
2. Over 5 years of industry experience

It was felt that five years of experience in the energy trading industry was adequate to understand the constructs and results quickly. From the author's experience in the industry five years is a reasonable amount of experience. Exposure to electricity trading was preferred but energy trading was also considered. Fortunately, all subjects had electricity trading experience.

5.2.6 Research Strategy

This case study uses a qualitative research strategy following [Kitchenham and Pfleeger 2003] that is exploratory and explanatory following [Robson 2002]. We employ a survey methodology that is a collection of standardized data from a specific population [Robson 2002]. The objective is to build a chain of evidence to verify the process of financial trading used in TRAMAS, and validate the simulation output produced by TRAMAS. It should be clear that verification of TRAMAS does not mean TRAMAS correctly reflects the workings of a real-world process, but rather the specification is complete and that errors have not been made in implementing the model [Macal 2005]. The goal of validation ensures that the model is useful and addresses the right problem, provides accurate information about the system being modeled and to determine if the model is useful [ibid.].

5.2.7 Research Methods

The online survey was restricted to respondents who had a username and password to access the survey. There was no interaction with respondents other than the emails sent to them with the login information by the author. All of the instructions were listed on the website and visible to them immediately. Respondents did not setup a market model and then run the simulation; they only reviewed the items listed in Section 5.2.3. This was because training would have been required for respondents had they been required to interact with TRAMAS, and given the time constraints for the experts, it was not feasible to do this. Also, the simulation would have taken time to complete and this also made it infeasible for the respondents to sit through.

The data collection method was of the second degree, where raw data was collected from respondents without the author interacting with the respondents [Runeson & Höst 2009]. There was a single source of data from the online website. The survey was open to respondents for 6 weeks. Once a respondent completed a survey they could not edit their responses, however before submitting their results they were asked to confirm before submitting. If they wanted to re-take the survey, their original responses were deleted; no respondents asked for a re-take.

Table 5-1 represents the six survey questions, E1-E6, each on a 5-point ordinal scale labelled SR1, SR2, SR3, SR4, and SR5: SR1= Missing Most Information, SR2=Contains Some Information, SR3=Contains Key Information but with Gaps, SR4=Contains Most Key Information, and SR5=Comprehensive Coverage; and three open-ended questions O1-O3. The survey below was designed with the following considerations [Kitchenham et al., 2002]:

1. Resilient to bias: The questions were designed so as not to sway any particular individual or group. It was designed to represent the reality of electricity trading.
2. Appropriate: Within the context of the sample of experts, the design was appropriate. Consideration had to be given to their busy work schedules yet it was felt the survey was complex enough, yet no more complex than it needs to be.
3. Cost-effective: The administration of the survey was very minimal. However, given the respondents busy schedules, it had to be created in a way to make it worthwhile for them to fill out.

Table 5-1: Expert Survey Questions

Label	Question
E1	What is your Expert Judgement of TRAMAS Model Components?
E2	What is your Expert Judgement of TRAMAS Model Assumptions?
E3	What is your Expert Judgement of TRAMAS Process Model?
E4	Looking at Chart 1. How well has TRAMAS represented the PRICES for the actual market?
E5	Looking at Chart 1. How well has TRAMAS represented the PRICE TRENDS for the actual market?
E6	Looking at the results in Tables 1-9. How well has TRAMAS represented an ACTUAL PJM market?
E7	From a scale from 1 to 5 where 1 is not very confident and 5 is very confident. How confident would you be to use TRAMAS (in different simulations) to help you trade in the REAL PJM market?
O1	Provide any feedback you may have about TRAMAS' Model Components.
O2	Provide any feedback you may have about TRAMAS' Model Assumptions.
O3	Provide any feedback you may have about TRAMAS' Process Model.

The survey was designed to take approximately twenty minutes.

5.2.8 Analysis

The following describes the complete process to analyse the survey data, since during the course of the analysis the data takes on several forms at different levels of abstraction. The different forms of information are numbered 1-7 in Figure 5-1. These numbers indicate the steps taken in the analysis process, starting from step 1 and ending in step 7.

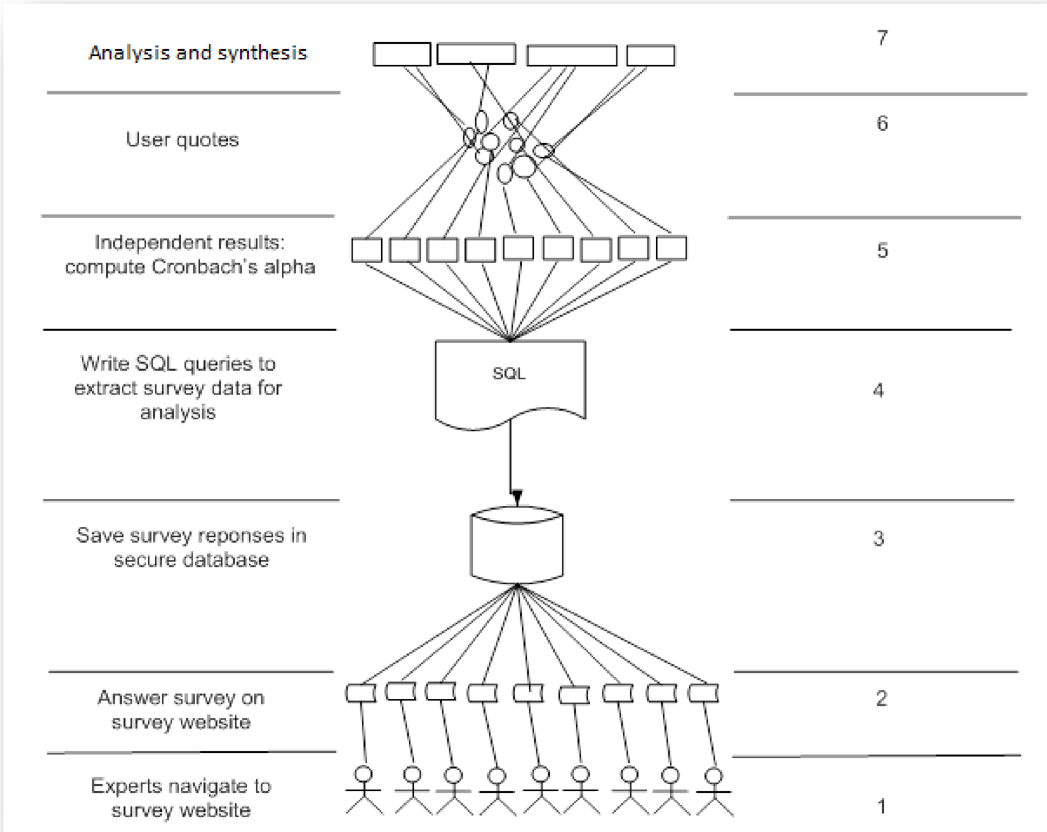


Figure 5-1: Transition in the Research Analysis Process

The first form simply indicates how the data originates; it starts by experts navigating to the survey website and logging in. The second form indicates the actual creation of the survey result. The third form transfers the information from the website to a secure survey database. The fourth form is the result set that is created from a SQL query. This result set is separated into individual results in the fifth form. The user quotes are extracted from the independent results in the sixth form. The seventh form is the analysis and synthesis of the user quotes. As the data takes on several forms it introduces additional validity threats to the results depending on the treatment performed in the transitioning stages. The validity threats and countermeasures are summarized in Table 5-2. The table shows the potential threats associated with each transition. Specifically, ρ_1 could introduce misconceptions, misunderstanding and lack of objectivity by experts in their responses. ρ_2 could introduce potential data transit error in the responses. ρ_3 could introduce incorrect SQL query for extracting the results for later analysis. ρ_4 could introduce incorrect categorization of the responses due to the previous threat, scale violation could be introduced because of a quantitative analysis of the responses, and potential non-respondent bias could affect the integrity of the responses. ρ_5 could introduce an incorrect extraction method for the user quotes. In addition, ρ_6 could introduce incorrect results due to the manual coding of users' comments in the analysis and synthesis. Countermeasures to these threats are discussed below.

Table 5-2: Transformation Between Information Forms in Survey Analysis

Transition	From	To	Treatment description	Threats
ρ_1	1	2	Native survey responses	Misconceptions, misunderstanding, lack of objectivity
ρ_2	2	3	Data written to a database table	Data transit errors
ρ_3	3	4	SQL query extracts result set from database	Incorrect query extraction
ρ_4	4	5	Categorized individual responses	• Incorrect categorization due to previous threat • Scale violation • Non-respondent bias
ρ_5	5	6	Extracted user quotes per expert	Incorrect extraction due to previous threat
ρ_6	6	7	Analysis and synthesis	• Incorrect results due to previous threats • Lack of objectivity • Misunderstanding • Misinterpretation of intent

The analysis performed in this study is inductive, which implies that the patterns, themes and categorizations come from the data itself and are not imposed on the data.

5.2.9 Threats to Validity

Based on the qualitative strategy chosen, the researcher himself acts as the instrument for the research and so a short discussion of the effects of the researcher involved is appropriate [Robson 2002].

The author was a Sr. Quantitative Analyst, in risk management, for over two years in a major electricity company and worked professionally in energy trading for close to 10 years. The responsibilities of a Sr. Quantitative Analyst is to develop trading models, perform valuation on trades, perform value at risk (VaR) analysis, and develop a core understanding of electricity markets in North America. This includes understanding all the fundamental factors affecting electricity prices and how these prices behave in certain times of days, on special holidays and weekends, etc., and to identify seasonal factors. It was a role that worked closely with electricity traders and required a deep understanding of how they performed trades and the tools and information they used that facilitated their trading.

To reduce the threats to this study, reasonable countermeasures are taken in the design of the study and throughout the study. Using the Lincoln and Guba model [Robson 2002] the threats to the validity and corresponding strategies are presented below. The model defines six strategies, which address three types of threats to validity: reactivity, researcher bias and respondent bias. The effects of these strategies on the threats to validity could potentially reduce the threats, have no effect, or increase the threats as shown in Table 5-3. Reactivity is not applicable because the researcher had no contact with respondents other than through one email. The researcher bias refers to the preconceptions of the researcher that have been brought into the study and could affect the way the researcher asks questions or interprets the answers. Respondents may also have biases that could influence their answers such as withholding information, giving answers they think the researcher wants or they look towards the study with suspicion [Karlstrom & Runeson 2006].

Table 5-3: Strategies to Deal with Threats to Validity

Strategy	Threats to Validity	
	Researcher Bias	**Respondent Bias**
Minimal involvement with respondents	Reduces threat	Reduces threat
Methodological Triangulation	Reduces threat	Reduces threat
Strict choice of respondents	No effect	Reduces threat
Online survey	Reduces threat	Reduces threat
Audit trail	Reduces threat	No effect

From the above table:

- *Minimal involvement with respondents* means that the researcher only sent one email to the respondents with survey login information without any future contact.
- *Methodological triangulation* means multiple methods were used to analyse qualitative methods.
- *Strict choice of respondents* means that the experts had to meet minimal criteria to participate in the survey.
- *Online survey* ensures certain steps are followed in a systematic way and restricts others i.e., preventing duplicate survey responses. It also gives respondents an opportunity to validate their own entries online.
- *Audit trail* is maintained for the survey i.e., all responses are stored in a secure database.

Table 5-4 discusses the countermeasures to the threats that exist as the data takes on different forms. An important threat to this study is scale violation. This occurs when an ordinal scale is converted to its numerical equivalents (i.e., 1 to 5). There are cases when this approach is reasonable, but it violates mathematical rules for analyzing ordinal data [Kitchenham & Pfleeger, 2003]. However, these authors state that there are two occasions where there is no real alternative to scale violation [p.26]:

1) If we want to assess the reliability of our survey instrument using Cronbach's alpha statistic [Cronbach 1951].

2) If we want to add together ordinal scale measures of related variables to give overall score of the concept.

Other countermeasures such as choosing minimal criteria for experts to minimize non-respondent bias is believed to be reasonable as experts who answered the survey are thought to be representative of those who did not answer the survey. However, this does not mean the bias is eliminated, it only means it is thought to be minimal in the study.

Table 5-4: Countermeasures to Validity Threats

Transition	Threats	Countermeasures
ρ_1	Misconceptions, misunderstanding, lack of objectivity	• strict criteria for respondents familiar with energy trading • information provided on survey website explaining the survey
ρ_2	Data transit errors	• fast internet connection that allows users to upload the survey site quickly • validation checking on the survey site before user submits survey
ρ_3	Incorrect query extraction	SQL syntax checking on query and tested on test data
ρ_4	Incorrect categorization due to previous threat • Scale violation • Non-respondent bias	• Previous countermeasures • Accept scale violation • Specific criteria for experts to minimize non-respondent bias
ρ_5	• Incorrect extraction due to previous threat	• Previous countermeasures
ρ_6	• Incorrect results due to previous threats • Lack of objectivity • Misunderstanding • Misinterpretation of intent	• Previous countermeasures • apply a simple coding scheme to minimize misunderstanding

Because reasonable attempts were taken to minimize the threats to validity of the results, it is believed that the validity of this study is sound.

5.2.10 Findings

The objective of the analysis was to answer the research questions R1-R3. Based on the survey results, what can we finally conclude from the responses? Overall results are shown in Figure 5-2. From this figure, the majority of the experts chose response SR4 for the questions, while slightly fewer chose SR5. For E1, seven experts chose SR4 while two experts chose SR5. E4-E6 questions ask how well TRAMAS represents the actual market: For E4 seven experts chose SR4, for E5 four experts chose SR4 and for E6 five experts chose SR4. Similar interpretation can be made for SR5 responses. These results are good for the following reasons (R1): a) no one chose SR1 and SR2, b) majority of the responses were SR4, c) some also chose SR5. This leads us to the first finding.

Finding 1: The overall view of majority of industry experts in energy trading is that TRAMAS contains most of the key information expected in a trade support application.

Furthermore, the distribution looks to be normally distributed: with peaks at SR4, and slightly lower in the tails (SR3 and SR5); this is good because it minimizes the scale violation threat [Kitchenham & Pfleeger, 2003].

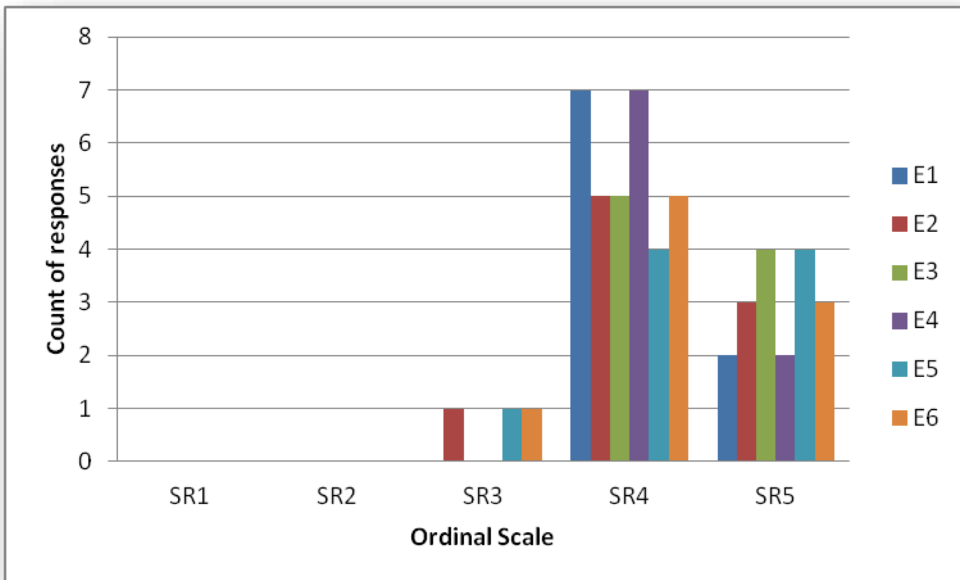


Figure 5-2: Overall expert responses

The proportion of the count of respondents is 6% for SR3, 61% for SR4 and 33% for SR5. Therefore, the majority of the respondents chose SR4.

To offer more insights into the results, Figure 5-3 to Figure 5-5 shows the responses by experts' role (R2). In Figure 5-3, the responses from five (5) senior analysts shows that no one chose SR1 or SR2 only one Sr. analyst chose SR3 for question E2 and E5. The majority of the analysts chose SR4 for all the questions, and two analysts answered SR5 for questions E3, while one analyst chose SR5 for E1, E2, E5 and E6.

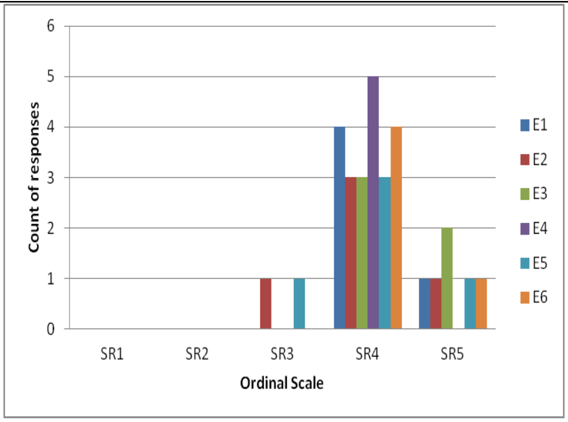


Figure 5-3: Five (5) Senior Analyst Expert Responses

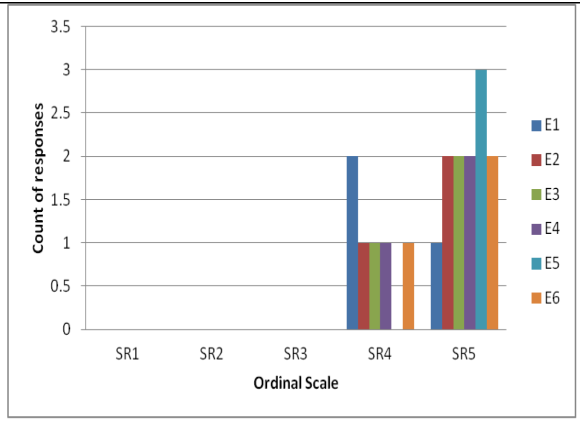


Figure 5-4 Three (3) Manager Expert Responses

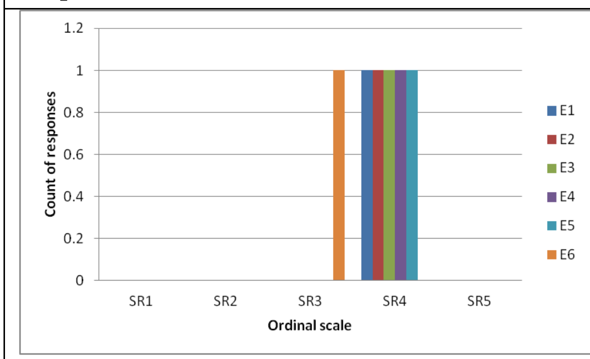


Figure 5-5 One (1) Director Response

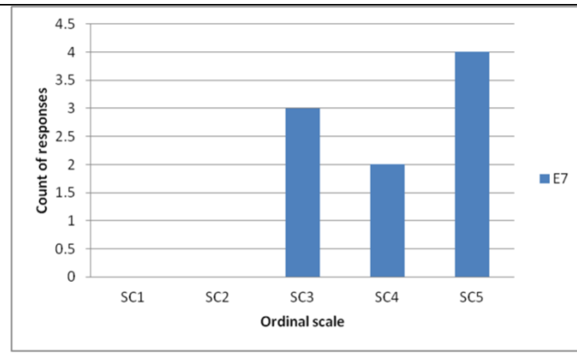


Figure 5-6 Question E7 Results

Figure 5-4 represents the responses from the three managers, and the results were better than the Sr. Analysts. None of the managers answered SR1-SR3 for any of the questions. The majority of the managers answered SR5. All managers answered SR5 for questions E5, which is important as this question asks how well the simulated results represent the actual market. Figure 5-5 shows the response from the one director that answered the survey. SR4 was the choice for questions E1-E5 while SR3 was chosen for E6. These are reassuring results and offer objective views on the feasibility of TRAMAS for use in the real market. This leads to the next finding.

Finding 2: There is no significant difference in the evaluations of TRAMAS by experts' business role.

From the above we also find that:

Finding 3: Managers found TRAMAS to be more useful than sr. analyst.

Finding 3 is interesting because in many cases analysts would be hands on with TRAMAS or at least more so than managers. This finding may suggest that from an operations perspective having a systematic approach to trade analysis could assist in helping to minimize trading risk for the business and possibly improve operations.

With respect to the users' experience with TRAMAS (R3), experts were asked question E7 with choices SC1=not very confident, to SC5=very confident. Table 5-6 shows that the majority of experts (4) would be very confident in using TRAMAS for the real PJM market. None of the experts chose SC1 or SC2. This result is important as it further adds to the credibility to TRAMAS for real market use. This leads us to the next finding.

Finding 4: Majority of the experts would be very confident in using TRAMAS for assistance in the real market.

We also computed the Cronbach's alpha [Cronbach 1951] in Table 5-5 for questions E1-E6 to determine the internal consistency of the test measure. Specifically, the internal consistency measures the extent to which all the items in the test, measure the same construct. This coefficient normally ranges from 0 to 1 but there is actually no lower limit to the coefficient [Cronbach 1951]. The closer the Cronbach's coefficient value is to 1 the greater the internal consistency of the items in the scale. [George & Mallery 2003] provide a useful rule of thumb: Alpha Value > 0.9 – Excellent, Alpha Value > 0.8 – Good, Alpha Value > 0.7 – Acceptable, Alpha Value > 0.6 – Questionable, Alpha Value > 0.5 – Poor, and Alpha Value < 0.5 – Unacceptable" (p. 231).

Table 5-5: Cronbach's Alpha

Reliability Coefficient	Value
Cronbach's Alpha	0.848
Index of measurement error	0.281

The computed alpha value of 0.848 says that the internal consistency of the items in the scale is good. It should be noted that a high alpha value does not necessarily mean the scale is unidimensional (i.e. measures a single construct). High values of the alpha coefficient could imply likelihood of unidimensionality of the test. The index of measurement error is also computed by subtracting the square of the Cronbach's alpha value from 1 to get 0.281. This value indicates that the coefficient has an error variance (random error) of 0.281 in the scores. This error is negatively correlated with the alpha value so as the Cronbach's alpha value increases, the fraction of the test score that is attributable to error will decrease [George & Mallery 2003].

As mentioned, the cases when the conversion to numerical values makes sense are when the distribution of the sample is approximately normal [Kitchenham & Pfleeger 2003]. When converting the data in other cases, the researcher risks having misleading results due to scale violation. From the above figures, an approximate normal distribution is not clearly visible but there does seem to be some semblance to a normal distribution (see Figure 5-2). For this reason, interpreting the results should be done with the appropriate caveats associated with potential scale violation. What can be concluded from the above analysis is that there is a definite tendency by the experts to mainly choose SR4 or SR5 for the questions, which would be a positive result for TRAMAS.

Open-ended Responses

Analysis of the open-ended responses offers further insights into the results. There were some interesting comments from the experts. The responses were coded as positive=1, neutral=0, or negative=-1. The coding decision was positive if the expert spoke positively about TRAMAS, it was neutral if they mentioned other changes to improve the model but did not say anything negative about TRAMAS and negative if they spoke negatively about TRAMAS. The responses are categorized with relation to the components, process, assumptions, results, and usefulness of TRAMAS. Table 5-6 presents the results of this categorization. There is no formal process for coding the responses. The coding depended on the author's evaluation to determine whether two different answers are equivalent or not [Kitchenham & Pfleeger 2003], this can cause additional bias to the categorization; however, this is felt to be minimal as the respondents were unambiguous in their remarks. As can be seen, the majority of the responses by the experts were positive. The numbers indicate the number of respondents.

Table 5-6: Comments' Categorization about TRAMAS

Areas	Positive	Neutral	Negative
	Director		
Components	1		
Assumptions	1		
	Manager		
Components	1	1	
Process	3	1	
Assumptions	1		
Results	2		
Useful	2		
	Sr. Analyst		
Components	9		
Process	6		
Assumptions	7		
Results	4		
Useful	5		

This leads us to the next finding.

Finding 5: All experts provided positive feedback on the areas relevant for TRAMAS, and managers and sr. analysts provided positive feedback on the usefulness of TRAMAS.

5.3 Discussion and Threats to Validity

This case study has presented results from industry experts who have evaluated the modeling constructs of TRAMAS and its results. Answers to research questions R1-R3 show that TRAMAS is positively viewed by the sample of experts surveyed. Specifically, the results were broken down by roles of Director, Manager, and Sr. Analyst. Feedback from all roles is positive with very few neutral comments, and no negative comments about TRAMAS. When asking experts if they would be confident in using TRAMAS in a real trading environment, a majority of the experts would be very confident in using TRAMAS in a real environment. These results bolster the belief that TRAMAS is a good representation of a trading environment, and would be effective for real-world use.

The computed Cronbach's alpha showed that the internal consistency of the items in the scale is also good and are measuring the same construct. These results, within the sample of nine respondents, show that TRAMAS would be useful for them in an industrial setting. Specifically, question E7 showed that the majority of respondents would be confident in using TRAMAS for industrial use. But a threat to these results is the small sample size of nine experts. However, as was discussed, the group surveyed is believed to be representative of a larger sample. This threat is likely to become more serious only if the survey was targeted to a more general audience and not experts because the variability of the respondents could have different effects on the results whereas domain experts have more specialized knowledge about the fundamentals of a particular domain that should not vary considerably.

Threats to the validity of the results were discussed, with key issues around scale violation concerns. The Cronbach's alpha value showed a value of 0.848 indicating that the internal reliability of the test is good with an error variance of 0.281. Therefore, while scale violation issues could lead to misleading results, trail of evidence from the experts, the internal consistency value, low measurement error and countermeasures for the threats, leads one to conclude that the results from this study are sound. Furthermore, [Kitchenham & Pfleeger, 2003] state that there are two occasions where there is no real alternative to scale violation [p.26]: 1) if we want to assess the reliability of our survey instrument using Cronbach's alpha statistic [Cronbach 1951]. 2) If we want to add together ordinal scale measures of related variables to give overall score of the concept.

The next case study looks at the results from TRAMAS to answer the research questions R4-R6, and validates the simulation output with actual market data.

5.4 Case Study #2: Trace Data Analysis (R4-R6) and Simulation Output Validation

5.4.1 Context

Bidding strategies are an important factor in trading. In order to make a successful trade, traders must have some strategy to help them determine how much of an asset to trade, at what price, at what time, whether to be a buyer or seller in the trade, or whether to trade at all. Forecast beliefs and personas of market participants will influence bidding strategies. Knowing how forecast beliefs and personas influence others' strategies could be additional information for the trader to use in forming his strategies. Therefore, it becomes critical that a trader have access to information to help him to form trading strategies. We will show how the evolutionary process of T-Evolve* is applied to help in determining the different types of trading strategies agents use to modify the prices they bid into the market. The *right* bid prices, those that are accepted in the market clearing process, effect profits earned in the settlement process.

5.4.2 Assumptions and Constraints

The following are the assumptions and constraints that apply to this case study.

1. Thirteen market models covering six different days were created and simulated by the author
2. Each market model contained twelve (12) agents and were simulated for ten (10) rounds
3. The data generated from the simulation was stored in a database that was secured with a username and password
4. The author did not manipulate the data in any way – all data was accessed and analysed by SQL queries written by the author
5. The historical data used by agents in the simulations ranged from November 4, 2011 to October 14, 2012

Given the above assumptions, what happens if they are false? And how does this impact the results? The first two assumptions of the study could be a limiting factor to the robustness of the results. The choice of the 13 market models and six days was mainly to capture as much variation in the days as possible. Specifically, for June 2 we analyse the effects on the market during good spring weather, on October 9 we analyse good fall weather, on June 4 and June 23 we analyse the effects of a weekday and weekend, July 1 we analyse the effects of a major storm and July 5 we analyse the effects of a heat wave. The dates were arbitrarily chosen by the author, the focus was to have as much variation in the events as possible. We could have chosen different events such as effects on prices on special holidays such as Christmas, Easter etc. Or even events such as the Super Bowl in the United States. These additional events could allow users to determine how prices vary during these different times and how to trade in these markets. We could have also chosen more market models with more agents. The ability to simulate a larger model may result in more variability in the results as there are more agents in the market trying to make a profit. The increase in the variability could offer different insights into how agent's trade and what prices they bid into the market. This could lead to more diversified trade plans for the user. More variability could also cause more variations in the similarity calculations between the actual prices and the simulated prices. Further, it could also result in lower probability of rewards for trades.

The date range for the data could have been extended beyond one year. The reason one year was adequate was due to the fact that it covers the four weather seasons. Had we extended the data beyond one year, we could have had more information on the impacts of seasonality on prices. In the future research we intend to simulate more market models with a wider selection of events to further capture the dynamics of agents' behaviours on market prices.

5.4.3 Study Design

The purpose of this case study is to answer the research questions: R4 – R6 and validate the simulated cleared prices (model output) with actual and average market prices by comparing the trends and similarity in the price magnitudes. Thirteen market models are simulated generating thirteen PMOs for six different days. Specifically, we simulate market models to predict market prices for the following: good weather (GW), weekday (WD), weekend (WE), and bad weather (BW) considered being non-normal weather conditions. The "Y" and "N" indicate whether the agents believe in the forecast (Y), or not (N). We choose two different GW days for spring and fall seasons, to see if seasonality has any impacts on the results. We also show how variations in the number of buyers and sellers affect trading outcomes. The choice of these types of days was to allow for enough variation in the forecasts and provide coverage on the types of days that traders normally have to deal with. All forecasts are for the east coast in the PJM area. Weather forecast and actual temperatures are for a representative city, Allentown, Pennsylvania, which is in the PJM area. The load forecast is for the PJM region.

Table 5-7 below describes the types of simulation scenarios that will be simulated. The simulation id (simid) is a system generated number uniquely identifying the simulation results for analysis. For each simid we used four types of agents: expagg, expnonagg, inexpagg, and inexpnonagg; a total of twelve agents are instantiated in the simulated market. All agents either believe in the forecast or they do not. Each simulation round is predicting the market prices that may occur on the forecast date. Agents learn from past wins and use this knowledge to adjust prices in subsequent rounds. The forecasted temperatures are used as the forecast for weather simulations. The actual temperatures are listed for informational purposes. The forecast type is simply a label to help identify the simulation scenario in the analysis below. The load forecast is also for the forecast date. Two different forecast data are used to show the potential differences in trading outcomes, as these are the two main forecasts used by electricity traders. The modification of the forecasts can be any modification a user chooses based on his beliefs about tomorrow. These values do not have to be the same for each simulation, the user can choose any modification to the forecast he wishes from the TRAMAS website. Furthermore, the table below shows how market model components can evolve to help the user view the market from different perspectives. For example, for June 4, four market models are simulated: 450745, 12737, 125112 and 527938. In 450745, the number of buyers is equal to sellers, the forecast variable is load, and all agents believe in the load forecast. The next model, 12737, the user[20] changes the forecast variable to weather, and modifies the agents' beliefs about the forecast thinking that it may be much warmer than forecasted, and the belief that there are equal number of buyers and sellers. What is justifying this change? It is a belief by a user of TRAMAS that tomorrows market participants may be using the weather forecast and they may have different beliefs about the weather forecast. The next model, 125112, the user believes that there may be more sellers than buyers, but that all believe in the weather forecast, and so on. Given the constantly evolving market, TRAMAS provides the flexibility to allow users to modify the market model in a way similar to how the real market may evolve.

Table 5-7: Simulation Scenarios

ID	Forecast Type	Buyers (b) / Sellers (s)	Forecast Variable	All Agents Believe in Forecast	Forecast Date (2012)	Forecast Temp.	Actual Temp.
281206	GW_Y	b=s	Weather	Yes	June 2	Low 13°C, High 23°C	Good spring weather (GW): Low 13°C, High 24°C
954178	GW_N	b=s	Weather	**No:** Expagg: L 22°C, H 40°C Expnonagg: L 24°C , H 37°C	Oct 9	Low 5°C, High 16°C	Good fall weather (GW2): Low 17°C, High 23°C

[20] Normally a user of TRAMAS would be making these changes, for this research they are the author's choices.

				Inexpagg: L 22°C, H 39°C Inexpnonagg: L 23°C, H 41°C			
450745	WD1_Y	b=s	Load	Yes	June 4	Low 9°C, High 23°C	Weekday (WD): Low 11°C, High 19°C
12737	WD2_N	b=s	Weather	**No:** Expagg: L 15°C, H 24°C Expnonagg: L 13°C , H 23°C Inexpagg: L 15°C , H 22°C Inexpnonagg: L 14°C, H 26°C	June 4	Low 9°C, High 23°C	Weekday (WD): Low 11°C, High 19°C
125112	WD3_Y	b<s	Weather	**Yes**	Jun 4	Low 9°C, High 23°C	Weekday (WD): Low 11°C, High 19°C
527938	WD4_N	b>s	Weather	**No:** Expagg: L 15°C, H 22°C Expnonagg: L 15°C , H 23°C Inexpagg: L 15°C, H 24°C Inexpnonagg: L 16°C, H 24°C	Jun 4	Low 9°C, High 23°C	Weekday (WD): Low 11°C, High 19°C
252884	WE1_Y	b=s	Load	Yes	June 23	Low 20°C, High 31°C	Weekend (WE): Low 17°C, High 29°C
220354	WE2_N	b=s	Weather	**No:** Expagg: L 22°C, H 41°C Expnonagg: L 24°C, H 37°C Inexpagg: L 22°C, H 39°C Inexpnonagg: L 23°C, H 41°C	June 23	Low 20°C, High 31°C	Weekend (WE): Low 17°C, High 29°C
533578	BW1_Y	b=s	Load	Yes	July 1	Low 23°C, High 33°C	Major storm in east coast, causing massive power outages (BW1): Low 19°C, High 38°C

404557	BW2_N	b=s	Weather	**No:** Expagg: L 22°C, H 40°C Expnonagg: L 24°C, H 37°C Inexpagg: L 22°C, H 39°C Inexpnonagg: L 23°C, H 41°C	July 1	Low 23°C, High 33°C	Major storm in east coast, causing massive power outages (BW1): Low 19°C, High 38°C
328797	BW3_Y	b>s	Weather	**Yes**	Jul 1	Low 23°C, High 33°C	Major storm in east coast, causing massive power outages (BW1): Low 19°C, High 38°C
69839	BW4_Y	b<s	Weather	Yes	Jul 5	Low 22°C, High 34°C	Heat wave (BW2): Low 20°C, High 42°C
186270	BW5_N	b<s	Weather	**No:** Expagg: L 15°C, H 22°C Expnonagg: L 15°C, H 23°C Inexpagg: L 16°C, H 23°C Inexpnonagg: L 15°C, H 22°C	Jul 5	Low 22°C, High 34°C	Heat wave (BW2): Low 20°C, High 42°C

Using the last round (round 10) of the simulation, the learning process becomes relevant as agents learn from their successes in previous rounds by adjusting the bid price with the β variable according to the bidding strategies, for the next simulation round. The round number is a parameter and can be easily modified by the user. In the future we plan to incorporate a more intelligent way to stop a simulation based on several criteria such as determining when the variation in the market cleared price is the smallest, by using the standard deviation parameter. There are also other ways such as determining if the profits decline in subsequent rounds and using this to stop. The evaluation of the trade plans and final trading decisions can then be made by users using the results from the analysis (step 6). The unit of analysis are the PMOs that include the chosen bidding strategies by agents. Before discussing the results, the next section discusses the effort distribution of simulating the thirteen (13) market models.

It should be noted that Table 5-7 is not a complete list of scenarios by any means. It shows what types of scenarios can be simulated in TRAMAS. A key point to note is that TRAMAS focuses on financial trading, which means that traders (buyer and sellers) do not exchange electricity physically, meaning if one trader sold 1 MW of electricity to another trader it is not a physical exchange rather a financial exchange of money after the trades are settled. This is different from a physical market which involves the physical delivery of electricity to the buyer of that electricity. Because electricity cannot be stored, as soon as it is produced, it must be consumed. Therefore, physical trading of electricity gets more complicated as there are many more considerations such as power generator efficiency and forced outages of generators which disrupt the distribution of electricity which is dependent on power lines. A recent analysis of forced outage[21] data of a major power utility[22] in North America from 2004-2013 is shown in Figure 5-7. The y-axis is the number of customers experiencing the outages and the x-axis shows the cause of the outages. As can be seen, birds are the cause of most of the outages, followed by trees fallen, equipment failure, adverse weather, corrosion or rot of equipment, tree branches, and so on. The factors are tabulated in Appendix G .

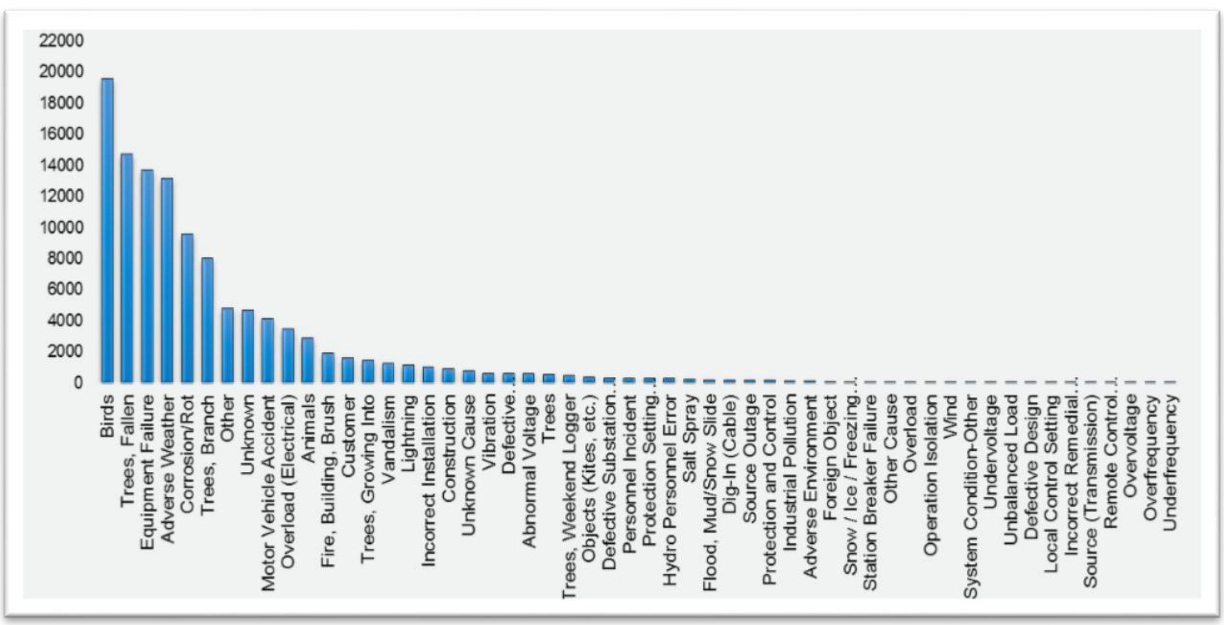


Figure 5-7: Analysis of Customer Forced Outages of a Major Utility (2004-2013)

[21] Forced outages are defined as any outage, that is not planned, that lasts for over 1 minute.
[22] This utility services close to 5 million people covering an area close to 1 million square kilometres.

Also, generating plants, transmission and distribution lines, substations and other equipment must be sized to meet the maximum amount needed by consumers at any time, in all locations [FERC, 2012, p. 2]. For the financial market, access to financial trade involves an investment grade credit to trade electricity [ibid.]. But this does not mean financial traders do not need to understand the physical electricity market, they do, because the physical market influences the financial market through changes in the real-time prices which is used to settle the trades of traders. The factors affecting outages shown in the above figure could also be used as forecast variables. While adverse weather can obviously affect the physical delivery of power to consumers, the influence of this in the financial could be higher prices but because traders in TRAMAS place there trades for tomorrow's market, one has to forecast in advance what the weather will do tomorrow and in this case weather forecast can play an important role in financial trading. But so can birds, but forecasting the migration path and nesting locations can be little harder to predict but could also be a variable that could affect prices in tomorrow's market. The weather is a key driver for electricity demand and supply [FERC, 2012, p. 42]. They indicate that seasonal peaks vary during regions, but that the highest peak levels in almost all regions of the United States occur during heat waves and more prevalent in the late afternoons. Other regions reach their peak load also during very cold weather. Electricity also varies between weekdays and weekends and the load can also vary between different weekdays for example, Mondays and Fridays may have different loads than in Tuesdays and Thursday [FERC, 2012, p. 43]. Other rises in electricity demand could be caused by economic factors such as increased tourism in an area in the summer. As such, traders follow closely weather trends, economic growth, and other factors to forecast power demand [Ibid.]. For these reasons load and weather forecasts are one of the key forecast variables used in the simulation scenarios but others can also be used.

Lastly, within the financial electricity trading market, traders do not know what or how others will bid in the market. Trading is completely anonymous and one trader would not know the expectations, choices or moves of another trader with certainty, but he can guess what another trader may do and this is exactly a key reason for using TRAMAS to simulate different scenarios that allow the user to simulate his beliefs on what others in the market may do and see how this affects the market price. Because there is no interactions between agents, and agents cannot influence directly other agents to behave in a specific way as in a real market, a user can however structure the market model in a way that could be a close representation of the real market.

5.4.4 Effort Distribution

The total effort required to generate results from the thirteen market models was 523 person minutes. Table 5-8 shows the allocation of effort in percentage terms per task. The simulation effort is the largest effort but this could be reduced given more powerful computer hardware. The analysis component in A4 could vary and dependent on how deep of an analysis a user wants to conduct. The other tasks in the five activities are self-explanatory and demonstrated in the sections to follow.

Table 5-8: Effort Distribution for Fifteen Market Models

Activity	Minutes	Effort
A1: Model Plan	**523**	
a. Market Belief Definition	33	6%
b. Forecast data selection	5	1%
c. Agents' selection	5	1%
d. forecast belief selection	25	5%
e. Agent instances' selection	5	1%
f. Choice of buy/sell action	5	1%
g. Analytical function selection	5	1%
A2: Simulation	230	44%
A3: Analysis	50	10%
A4: Evaluation		
PMO 1	10	2%
PMO 2	10	2%
PMO 3	10	2%
PMO 4	10	2%
PMO 5	10	2%
PMO 6	10	2%
PMO 7	10	2%
PMO 8	10	2%
PMO 9	10	2%
PMO 10	10	2%
PMO 11	10	2%
PMO 12	10	2%
PMO 13	10	2%

A5: Selection	25	5%
Other:		
Publishing and Saving trade report	5	1%
Total		**100%**

5.4.5 Subjects

This case study does not involve human subjects; it is a quantitative analysis of agents' trace data.

5.4.6 Research Strategy

We extract information in the PMOs associated with market models by using SQL queries[23]. These queries can be easily modified by users. The extracted information is used to answer the research questions R4-R6. Therefore, we approach this case study using a quantitative research strategy [Robson 2002].

5.4.7 Research Methods

The main source of information is the agent bidding strategies that are captured in a database table (0, Table 6-1). Bidding strategies in each PMO, and the associated profits, are extracted from tables using SQL queries. In the future, we plan to automate the extraction of this information from the TRAMAS website.

The simulation output validation uses actual real-time price in the forecast date (column C[24]), and average historical real-time price up to the day before the forecast date. The reason behind using the average prices is that in a typical setting TRAMAS would predict the actual market prices for the forecast date; the average historical are thus the expected prices on the forecast date. For the purposes of this research having actual prices on the forecast date facilitates the validation of the model prices.

[23] Navigate to my research page to view the SQL queries used to analyse the agent trace data: http://people.ucalgary.ca/~smaurice/PhD%20Research-SQL%20Queries.pdf.
[24] See http://people.ucalgary.ca/~smaurice/phd_research_data.xls.

5.4.8 Analysis

The analysis in this case study is of the inductive type, meaning that patterns and themes come from the data. As discussed in the previous case, during the analysis process the information takes on several forms at different levels of abstraction. These forms are shown in Figure 5-8. The first form (1) is the actual market model as chosen by the user. The second form (2) is the stored simulation results from the agents' actions. The third form (3) is the extracted data from the SQL data in raw form. The fourth form (4) is the average of the bidding strategies' results. The fifth form (5) is the results.

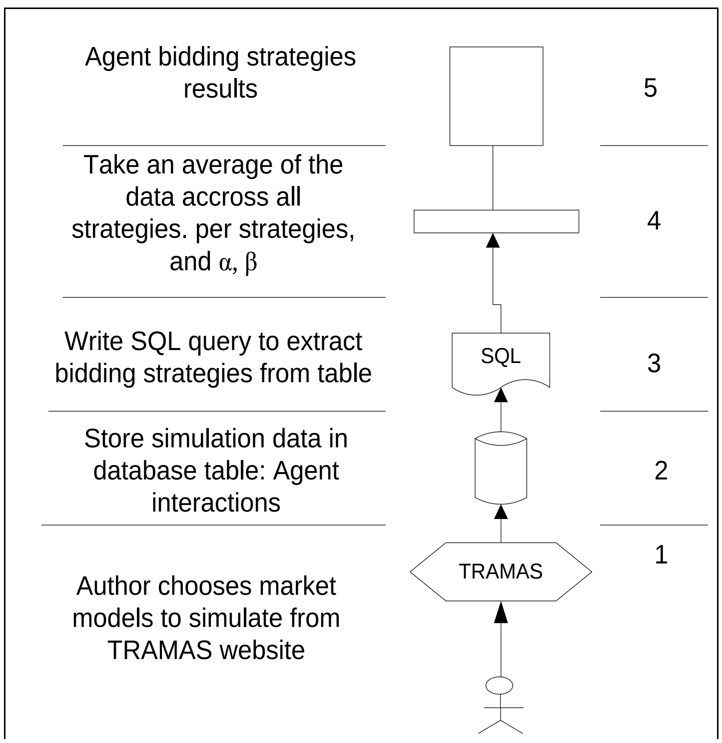


Figure 5-8: Transition of data in the analysis process

Each additional transition introduces validity threats to the results. These threats are summarized in Table 5-9. The countermeasures to these threats are also discussed in a later section below; we discuss how the effects of these threats can be minimized. From the table below, τ_1 transition may introduce lack of objectivity because it is the author's model choice, as well omission of data, missing market components and the market model not being representative of the real market all could threaten the validity of the results. τ_2 transition may introduce incorrect results due to previous threats, as well the query may not be correct. τ_3 transition could add further threats due to previous threats as well as averaging of the results could cause results to be misinterpreted due to information loss. τ_4 transition introduces the threats from previous transitions.

Table 5-9: Transition in Trace Data Analysis

Transition	From form	To Form	Treatment description	Threats
τ_1	1	2	Captured Agents' actions	• Lack of objectivity • Omission of data • Missing market components • Market model not representative of real market
τ_2	2	3	SQL extraction	• Incorrect results due to effects of previous threats • Incorrect query
τ_3	3	4	Average results	• Incorrect results due to effects of previous threats • Averaging causes results to be misrepresented due to information loss
τ_4	4	5	Agent bidding strategy results	Incorrect results due to effects of previous threats

5.4.9 Validation

The objective of this section is to conduct power price similarity (PPS) analysis between the simulated cleared (model) prices, and the average and actual prices. While there is no one method to conduct output validation it is the chain of evidence, preferably statistical evidence for quantitative data, that is presented in an effort to increase the user's confidence in the results [Robson 2002; Marks 2007].

Similarity Analysis

Figure 5-9 shows the similarity results for each of the PMOs[25]. The graphs should be self-explanatory in that we are looking for the simulated prices (red) to follow a similar trend of the actual (blue) and avg. prices (green).[26] These graphs are supplemented by the similarity numbers

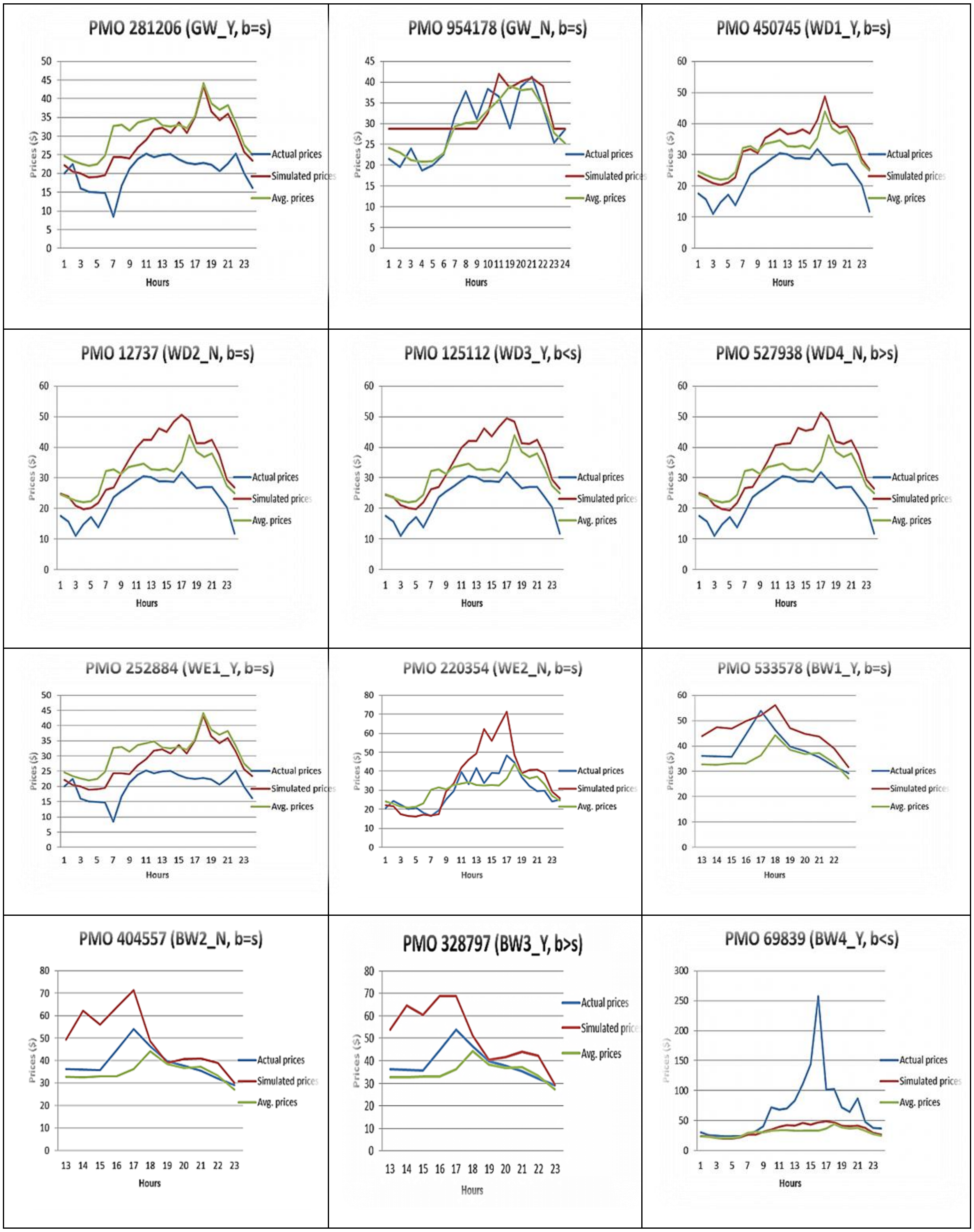
[25] Navigate to my research page to view the raw data: http://people.ucalgary.ca/~smaurice/phddata_research_analysis.xlsx. Refer to tabs [Simulation_id]-raw.

[26] Actual prices are the real-time prices on the forecast date. And the average prices are the historical real-time prices up to the day before the forecast date. An hour by hour comparison is done using the PPS measure.

in Table 5-10. In this table, the simulated prices show a 62% average similarity with actual prices and 77% with average prices. The highest similarity with actual prices is in 533578 (BW1_Y) of 82% and 92% with average prices in 450745 (WD1_Y). The lowest are in 12737 (WD2_N) with 49% and in 328797 (BW3_Y) of 53% for actual and average prices, respectively.

The indication from the graphs is that for most forecasts the model prices follow a similar trend to the actual and historical prices, with the exception of 220354 (WE2_N), 69839 (BW4_Y), and 186270 (BW5_N). These models deal with weekend and bad weather days. The spike in prices shows the volatility in these days. Unfortunately, TRAMAS did not fully capture this volatility but this is not a bad thing. Specifically, for BW5_N, it shows that the agents' forecast beliefs were way below the actual temperatures, in that the agents' beliefs were that weather would be normal, but the actual temperatures turned out to be very hot (see Table 5-7). So in this case we should not expect TRAMAS to predict the market accurately when agents hold the wrong belief, and most probably traders in the real-market believed in the forecast. It may also be that modifications of the forecast belief may help to improve this trend if traders incorporated the potential spike in future prices in their modification of the forecast. Thus accurate forecast beliefs could help in establishing better predictions about future prices that may lead to better trading decisions.

Interestingly in 220354 (WE2_N) agents do not believe in the forecast and this may explain why we are seeing a slightly better similarity with actual prices in this model. Also in the simulation buyers equal sellers and this may be what the actual market contained. In that the real market likely was split between buyers and sellers. However, the volatility may be too high for some traders to make profits and there were some emergent behaviour that the simulation did not capture.


PMO 281206 (GW_Y, b=s)
PMO 954178 (GW_N, b=s)
PMO 450745 (WD1_Y, b=s)
PMO 12737 (WD2_N, b=s)
PMO 125112 (WD3_Y, b<s)
PMO 527938 (WD4_N, b>s)
PMO 252884 (WE1_Y, b=s)
PMO 220354 (WE2_N, b=s)
PMO 533578 (BW1_Y, b=s)
PMO 404557 (BW2_N, b=s)
PMO 328797 (BW3_Y, b>s)
PMO 69839 (BW4_Y, b<s)
Prices ($)
Hours
Actual prices
Simulated prices
Avg. prices

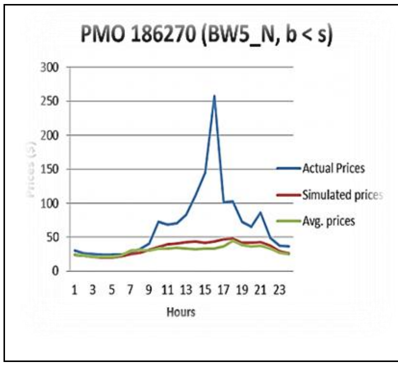


Figure 5-9: Trend Comparisons

While it is reassuring that the similarity numbers are higher for other simulations, they nonetheless show that in volatile times TRAMAS may not be capturing behaviours very accurately but that this could be mitigated by users modifying the forecast more accurately. In volatile periods having the most accurate forecast beliefs become even more important, but also more difficult to achieve. This leads us to the finding.

Finding 6: When markets are volatile, TRAMAS may not produce prices that are close to the actual prices but this may be mitigated by establishing more accurate forecast beliefs.

Table 5-10: Similarity Between Actual and Avg. Prices

SIMID	Forecast Type	Actual prices and simulated prices	Avg. prices and simulated prices
281206	GW_Y	60%	90%
954178	GW_N	64%	74%
450745	WD1_Y	60%	92%
12737	WD2_N	49%	82%
125112	WD3_Y	52%	84%
527938	WD4_N	54%	86%
252884	WE1_Y	65%	79%
220354	WE2_N	68%	64%
533578	BW1_Y	82%	70%
404557	BW2_N	73%	59%
328797	BW3_Y	68%	53%
69839	BW4_Y	52%	85%
186270	BW5_N	55%	87%
Average		**62%**	**77%**

Table 5-11 shows further analysis which determines the statistics of the simulated prices. These results are presented for completeness, and are required for analysis of this type [Kitchenham & Pleeger 2003]. These descriptive statistics were computed for all simids. The standard error results show the variability in the simulated prices and the mean shows the expected value of these prices, having these two values similar to the actual prices is good and most results show this. However, consider 69839 (BW4_Y) and 186270 (BW5_N) that show the standard error values for the simulated prices of $1.00 and $5.37 and $0.97 and $4.94, respectively. These numbers vary considerably from the actual values. The kurtosis and skewness values for simulated prices are similar for 69839 than 186270 indicating that the model prices are not capturing the distribution of the actual prices. This further indicates that these models are not properly capturing behaviours in the real market and so further adjustments to the market models in the next iteration could be needed.

On the positive side the results from the TRAMAS' models are not so bad. They show that only one model (12737) is below a 50% similarity threshold. The additional descriptive statistics offer additional information on the statistical properties of the model prices, which are similar to the actual prices, with few exceptions, but this is to be expected when a market model is not an accurate representation of the real market. For the analysis to follow, these results should provide the reader with a high level of confidence that the results from TRAMAS are reliable.

Table 5-11: Descriptive Statistics

281206 (GW_Y)			954178 (GW_N)			450745 (WD1_Y)		
Statistics	**Simulated Prices**	**Actual Prices**	**Statistics**	**Simulate d Prices**	**Actual Prices**	**Statistics**	**Simulate d Prices**	**Actual Prices**
Mean	28.65	20.53	Mean	38.40	30.29	Mean	32.46	23.32
Standard Error	1.38	0.82	Standard Error	1.44	0.75	Standard Error	0.82	1.34
Kurtosis	-0.70	0.78	Kurtosis	1.20	-0.98	Kurtosis	-0.94	-1.16
Skewness	0.36	-1.08	Skewness	0.69	-0.11	Skewness	-0.11	-0.56
Min	19.05	8.42	Min	0	18.74	Min	20.44	11.17
Max	43.34	25.28	Max	71.36	41.32	Max	48.76	31.81
Count	27	27	Count	77	77	Count	92	92

12737 (WD2_N)			125112 (WD3_Y)			527938 (WD4_N)		
Statistics	**Simulate d Prices**	**Actual Prices**	**Statistics**	**Simulated Prices**	**Actual Prices**	**Statistics**	**Simulate d Prices**	**Actual Prices**
Mean	34.71	23.31	Mean	34.48	23.32	Mean	33.49	22.77
Standard Error	2.09	1.34	Standard Error	1.00	0.66	Standard Error	1.19	0.80
Kurtosis	-1.52	-1.16	Kurtosis	-1.50	-1.17	Kurtosis	-1.36	-1.28
Skewness	-0.07	-0.56	Skewness	-0.09	-0.53	Skewness	0.07	-0.41
Min	19.88	11.17	Min	19.89	11.17	Min	19.39	11.17
Max	50.51	31.81	Max	49.38	31.81	Max	51.33	31.81

Count	24	24

Count	96	96

Count	66	66

252884 (WE1_Y)

Statistics	Simulated Prices	Actual Prices
Mean	37.00	29.84
Standard Error	1.19	1.06
Kurtosis	-1.35	-0.95
Skewness	0.14	0.37
Min	22.99	16.42
Max	55.65	48.40
Count	72	72

220354 (WE2_N)

Statistics	Simulated Prices	Actual Prices
Mean	41.82	32.98
Standard Error	2.10	1.14
Kurtosis	-0.61	-0.76
Skewness	0.12	-0.03
Min	16.18	16.42
Max	71.39	48.4
Count	53	53

533578 (BW1_Y)

Statistics	Simulated Prices	Actual Prices
Mean	45.68	38.85
Standard Error	0.94	1.03
Kurtosis	0.56	0.15
Skewness	-0.61	0.85
Min	31.7	29.19
Max	56.15	53.96
Count	44	44

404557 (BW2_N)

Statistics	Simulated Prices	Actual Prices
Mean	49.24	38.85
Standard Error	2.15	1.19
Kurtosis	-0.99	0.21
Skewness	0.33	0.86
Min	30.23	29.19
Max	71.39	53.96
Count	3	33

328797 (BW3_Y)

Statistics	Simulated Prices	Actual
Mean	51.34	38.85
Standard Error	1.90	1.03
Kurtosis	-1.14	0.16
Skewness	-0.03	0.85
Min	29.27	29.19
Max	68.81	53.96
Count	44	44

69839 (BW4_Y)

Statistics	Simulated	Actual
Mean	34.19	66.72
Standard Error	1.00	5.37
Kurtosis	-1.52	5.56
Skewness	-0.07	2.17
Min	20.17	23.78
Max	49.24	257.18
Count	94	94

186270 (BW5_N)

Statistics	Simulate d Prices	Actual Prices
Mean	33.62	63.91
Standard Error	0.97	4.94
Kurtosis	-1.54	6.85
Skewness	-0.11	2.28
Min	19.89	23.78
Max	48.18	257.18
Count	93	93

5.4.10 Threats to Validity

We use the Lincoln and Guba model [Robson 2002] to further analyse the threats to validity and explore strategies to deal with these threats as discussed in case study #1. Table 5-12 summarizes the specific countermeasures to the validity threats.

Triangulation refers to having multiple sources of information for the study. Different information is attained thirteen different ways for six different types of days, which further increases the validity of the results. A summary of the methods are:

1) Data triangulation: multiple sources of data are used to generate different PMOs

2) Theory triangulation: multiple market models are presented that incorporate different market beliefs to generate the different PMOs.

An extensive and structured database record is kept of all agents' actions for each simulation in the form of an *audit trail*. A systematic process is applied to extract the data from the database tables.

Validation of the simulation output with real data and expert reviews that confirm the comprehensiveness of the modeling constructs and results should further increase the validity of the results.

Table 5-12: Threats to validity strategies

Strategy	Researcher Bias
Triangulation	Reduces threat
Audit trail	Reduces threat
Validation	Reduces threat

Table 5-13 discusses the countermeasures to the threats shown in Table 5-9.

Table 5-13: Countermeasures to Validity Threats

Transition	Threats	Countermeasures
τ_1	• Lack of objectivity • Omission of data • Missing market components • Market model not representative of real market	• Use several market models with varying beliefs and data • Establish baseline market model • Validation
τ_2	• Incorrect results due to effects of previous threats • Incorrect query syntax	• Previous countermeasures • SQL syntax error checking
τ_3	• Incorrect results due to effects of previous threats • Averaging causes results to be misrepresented due to information loss	• Previous countermeasures
τ_4	• Incorrect results due to effects of previous threats	• Previous countermeasures

The application of the methodology to generate PMOs based on different market models makes it possible to increase the transferability of the study to other domains. Incorporation of different forecast beliefs and personas shows the flexibility of the technology to capture users' market beliefs in a systematic way. In summary, multiple countermeasures are employed that are reasonable to ensure the validity of the results. Therefore, it is believed that the validity of the study is sound.

5.4.11 Results

Table 5-14 shows the average profits over all of the strategies used by each agent (see Appendix E for more details). Specifically, the profits are summed over all strategies A-I for each hour 1 to 24. To help interpret the results, Table 6-9 shows a generalization of the bidding strategies shown in Table 3-13 with the exception of the superscripts and subscripts on the α and β parameters. Each agent type uses one of these bidding strategies, which we analyse below. Based on the results, we can see that agents with no experience consistently made positive profits. The only exception was 12737 and 69839. Further analysis of these models showed that inexpagg and inexpnonagg were designated as buyers and expagg and expnonagg as sellers, whereas for the other models it was the reverse. This indicates that agents that do not have much experience should consider being sellers, if they are buyers they are likely to lose. This leads to the next finding.

Finding 7: Traders with little experience could profit more from being sellers, rather than buyers.

The highest profits are made in BW3_Y by both inexpagg and inexpnonagg agents of $1730.35 and $1503.42, respectively. Interestingly, expagg and expnonagg mostly made negative profits. Expagg made positive profits in BW4_Y of $492.31 and expnonagg made positive profits of $864.69 in WD2_N. The highest loss is taken by expagg of -$5786.23 in BW2_N. These results are interesting for several reasons. First, experience, it seems, does not necessarily lead to more profits; in fact, inexperienced aggressive and non-aggressive agents made the most profits while experienced agents did not.

Table 5-14: Profits from Strategies

Simulation ID	Forecast Type	Expagg	Expnonagg	Inexpagg	Inexpnonagg
281206	GW_Y	-266.11	461.60	298.62	691.12
954178	GW_N	-3246.12	-998.65	723.74	-514.81
450745	WD1_Y	-6.15	-389.67	-44.74	336.02
12737	WD2_N	375.07	864.69	-485.28	-797.89
125112	WD3_Y	-380.06	-375.14	482.48	763.37
527938	WD4_N	-178.75	-1374.88	424.52	235.47
252884	WE1_Y	-1116.92	-901.26	1041.07	874.01
220354	WE2_N	-5548.97	-2188.61	1472.71	1165.17
533578	BW1_Y	-1026.14	-971.29	1190.69	889.86
404557	BW2_N	-5786.23	-2684.50	1529.52	1491.25
328797	BW3_Y	-1461.27	-2186.85	1730.35	1503.42
69839	BW4_Y	492.31	854.81	-107.80	-196.00
186270	BW5_N	-67.14	-139.03	275.08	895.94
Total		**-1401.27**	**-771.44**	**656.23**	**564.38**

This aligns with the results of [Gode & Sunder, 1993] that showed efficiency in a market is mostly derived from the structure of the market, independent of the traders' intelligence, motivation or learning. The market discipline imposed on traders is more important than the intelligence, motivation, or learning for allocative efficiency [Gode & Sunder, 1993]. This leads us to the finding.

Finding 8: Experience and learnings derived in a market is no guarantee of success.

Second, the high losses for BW2_N for expagg may show that high prices during bad weather results in more riskier trades because bad trades can cause larger losses (or higher profits) due to the higher spreads in prices and experienced and aggressive traders are willing to take the risk for higher pay off. These results indicate that the difference between risk neutral and risk averse traders may be due to how aggressive a trader is, not necessarily how much experience they may. Recall in TRAMAS, aggressiveness is captured in the β parameter which allows agents to adjust the price from round 1 by marking it down (sellers) or marking it up (buyers). For sellers, trying to undercut other sellers to attract buyers is considered an aggressive behavior, likewise for buyers who try to offer the highest price for a good is also considered aggressive behavior. This leads to us to the next finding.

Finding 9: Experienced and aggressive traders are likely to be more active in non-normal conditions due to the possibilities of higher rewards.

Third, it may be that expagg have taken the risk, as they should, but in this case their risks ended up with losses. But this is exactly what traders need to prepare for; in times when prices are the most volatile the chances of making the most money are the highest but it is also a time when heavy losses are possible. From Figure 5-10 note the erratic profits and losses for the expagg agent especially in the BW2_N, further indicating that these agents are acting aggressively and willing to take on the risk of profit losses. This is exactly the insight that TRAMAS provides before any *real* money is lost or gained. This leads us to the next finding.

Finding 10: Experienced and aggressive traders are likely to be more accepting of the risk of losses in volatile markets.

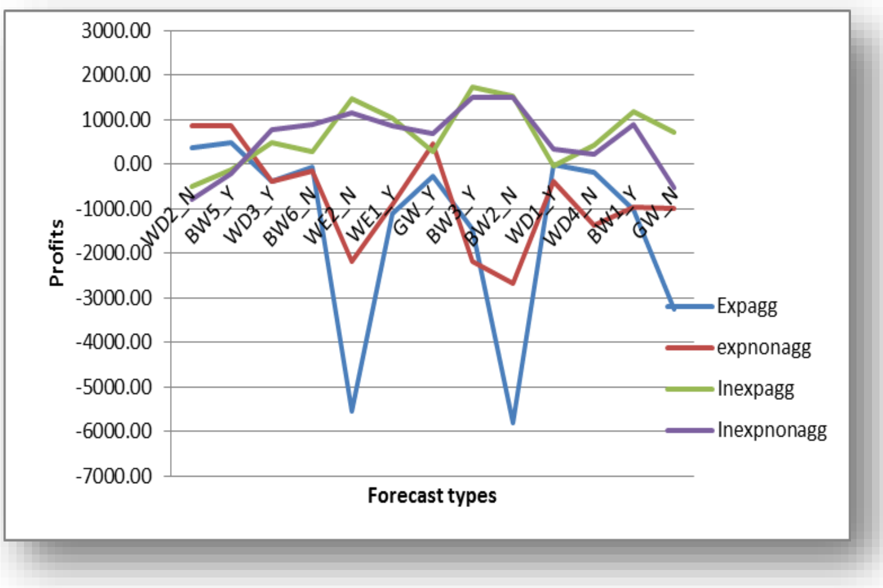


Figure 5-10: Profits from Strategies

The probability of rewards also shows that on average sellers would likely do better than buyers with an average probability of reward of 61% for buyers and 65% for sellers.

Table 5-15 shows the profits by buyers and sellers[27]. We compare the profits generated by the simulation with the actual results to see whether traders would have profited from the suggested trades by TRAMAS. The actual results are computed by taking the difference between the real-time price and the simulated cleared price times one megawatt (MW[28]). The simulated profits are computed by taking the difference between the simulated cleared price and the average of the historical prices less a day from the forecast date times 1 MW[29]. One can immediately see that the simulated results do a very good job in predicting the positions that would lead to positive profits in the actual market. Specifically, in the simulations, TRAMAS correctly predicted that buying would be a losing position to take in the real market, and indeed, in the actual (real) market buyers mostly lose. TRAMAS predicted sellers would make positive profits and indeed in the actual markets sellers profited. So for both buyers and sellers, TRAMAS successfully predicted the position that traders should take ten out of the thirteen times, which is approximately a 77% success rate. For the actual trades, refer to Appendix D The probability of rewards also shows that on average sellers would likely do better than buyers with an average probability of reward of 61% for buyers and 65% for sellers.

Table 5-15: Actual and Simulated Profits: Buyers and Sellers

		Actual Profits		Simulated Profits			
Simulation ID	**Forecast Type**	**Buyers**	**Sellers**	**Buyers**	**Sellers**	**Prob. Reward Buyers**	**Prob. Reward Sellers**
281206	GW_Y	-182.17	37.17	75.62	-3.67	61%	65%
954178	GW_N	-207.97	207.97	-159.12	159.12	62%	63%
450745	WD1_Y	-221.86	221.86	-34.69	34.69	61%	65%
12737	WD2_N	-273.63	273.63	-86.46	86.46	60%	65%
125112	WD3_Y	-267.91	267.91	-80.74	80.74	60%	65%
527938	WD4_N	-270.76	236.14	-83.59	55.91	60%	65%
252884	WE1_Y	-171.97	171.97	-151.77	151.77	58%	66%
220354	WE2_N	-146.98	163.32	-126.79	176.35	62%	64%
533578	BW1_Y	-75.08	75.08	-151.89	151.89	59%	66%
404557	BW2_N	-114.28	114.28	-127.09	176.26	62%	64%
328797	BW3_Y	-137.38	137.38	-157.14	157.14	62%	63%
69839	BW4_Y	787.84	-787.84	-83.86	83.86	60%	65%
186270	BW5_N	796.87	-796.87	-74.83	74.83	60%	65%
Total		**-50.50**	**37.94**	**-108.73**	**119.73**	**61%**	**65%**

[27] Navigate to my research page to view the raw data: http://people.ucalgary.ca/~smaurice/phddata_research_analysis.xlsx. See tab "Profits".
[28] Using 1 MW is just to simplify the calculations without losing any generality; other values can easily be used.
[29] See Appendix D for the trade plans.

The actual profits show that for BW4_Y and BW5_N buyers made the most profit, this would make sense since buyers are long prices (i.e. expect prices to rise) and indeed when there is bad weather electricity prices tend to rise, however, for the simulated prices buyers lost money. These differences could be due to the volatility in the market in times of bad weather and TRAMAS's inability to properly capture emergent behaviours in these dynamic markets. But, as mentioned, the difficulties in capturing market volatility are a challenge for any model and this is the main reason why predicting price outcomes in financial markets are extremely difficult.

Finding 11: Simulation results from TRAMAS may not necessarily match what happens in the actual market because the simulation is based on a model, which will never represent an actual market exactly, especially in non-normal conditions.

Based on the results in Table 5-15, it's clear that sellers have a higher probability of reward than buyers in the simulated profit section. Specifically, 252884 and 533578 have the highest average probability of reward for sellers at 66% and the profits generated are \$151.77 and \$151.89, respectively. While 533578 profits are higher, technically the final trade plan should be therefore 533578 (see Appendix D as it provides the highest probability of reward and generates the highest profits. We also validate this result with actual prices. In the same table, we validate the simulated results with actual data. So, had the user chosen the trade plan from 533578, he would have made an actual profit of \$75.08. In this way of looking at the average profits from trade plans in PMOs and their average probability of reward TRAMAS can help to provide decision support to traders in making final trading decisions.

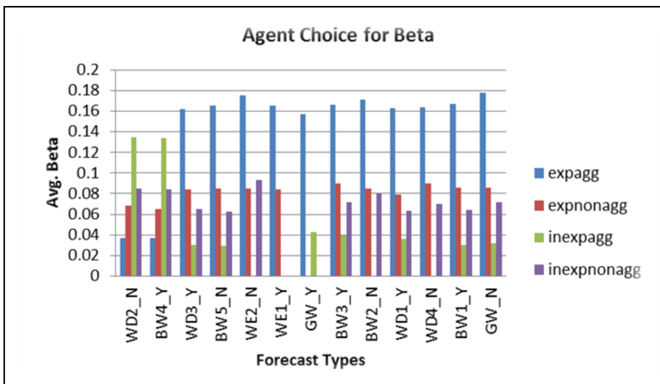
The numbers for buyers and sellers is mostly in the 60% range. What makes these numbers interesting is that they are not high, rather a value that is usually comparable to what one could expect in the real market[30]. Higher numbers would of course be better, but in trading there is no sure thing because the market is constantly evolving and while high probability numbers are good, they may also give a trader a false sense of security which is not what should be implied from these probability numbers. The probability numbers are more for informational purposes and should be used in conjunction with other information. Also, the magnitude of the profits is

[30] Based on the author's experience on the trading floor at a major utility.

also in line with what traders can expect from a 1 MW trade, assuming they win the trade. Interestingly, it is BW5_N that makes the most profits for buyers. This may be because there is more volatility in the prices in bad weather and traders make money during volatile times when price spreads are likely to be the widest.

Additional analysis was done to compare the strategy variables α and β with the forecast and agent types in Figure 5-11. They show average variations in these two variables for the last round of the simulation. For the first graph, the β value for expagg is the highest and this is consistent across all forecast types, as expected, but interestingly the values for the inexpnonagg and expnonagg are similar, which may suggest that while inexperience may not be as relevant for trading in this market, too much aggressiveness does not always payoff, in fact, in our results, being too aggressive in times when the market is non-normal (i.e. in bad weather conditions) may lead to large losses. This was the case for the expagg in 404557. This leads us to the next finding.

Finding 12: In TRAMAS, knowing when to be aggressive and when not to be aggressive is also important for success.



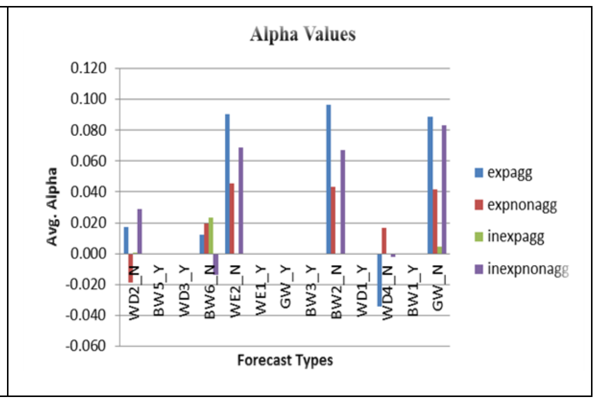


Figure 5-11: Strategy Variables

We also performed analysis on the α parameter shown in the above figure. While this parameter is user driven, the graph shows how this parameter varies for the forecast types for each agent type during the simulation round. The variation of this parameter shows how forecast beliefs

change in the rounds. From Figure 5-11, agents who believe in the forecast (α=0) have more success than agents who do not believe in the forecast. In fact,
Table 5-16 shows that expagg agents make the most losses when they do not believe in the forecast, similarly for expnonagg agents. The inexpagg agents are almost split between the two beliefs, while the inexpnonagg agents made most money when they believe than when they do not believe.

Table 5-16: Avg. Profits by Forecast Beliefs

Beliefs	Expagg	Expnonagg	Inexpagg	Inexpnonagg
Believe	-537.76	-501.12	655.81	694.54
Do not believe	-2408.69	-1086.83	656.72	412.52

Even though these losses are fairly large, not believing in the forecast lead to gains for other agent types. But what can be seen here, in Figure 5-12, is that forecast beliefs can have drastic effects on profits for the types of behaviours that may exist in the real market. Indeed, agent types, forecast beliefs, and experiences lead to differences in results that have been shown to be consistent with what may actually happen in the real market. Properly formulating beliefs can offer an advantage to traders even when markets are volatile by showing that it may be best not to participate in the real market. This leads us to the next finding.

Finding 13: Beliefs about the forecast can have drastic impacts on profits in this market.

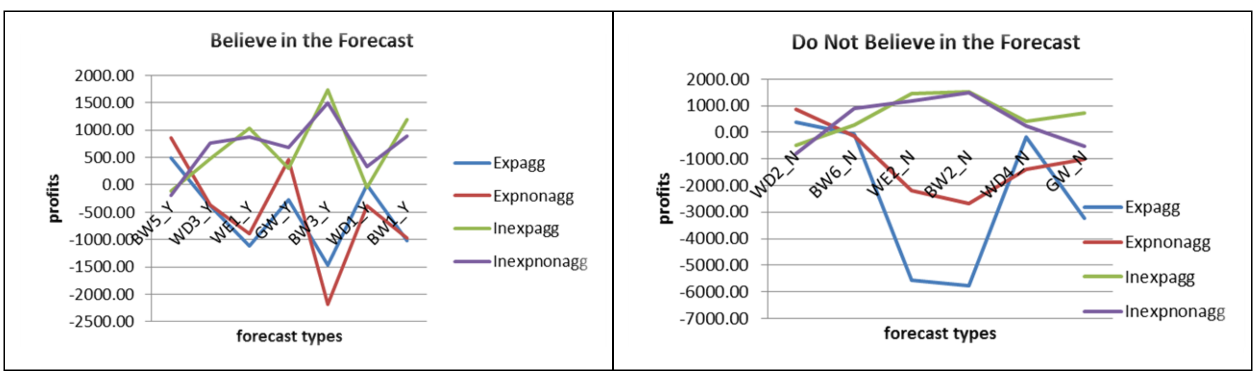


Figure 5-12: Forecast Beliefs and Profits

5.4.12 Summary and Conclusions

The results of case study #2 show that bidding strategies driven by personas and forecast beliefs can be helpful in establishing a trading plan. What this shows is that it is a reasonable expectation that traders in the real market will have different strategies based on their forecast beliefs and personas and those differences in beliefs and personas can lead to different impacts on profits. However, given that the market is constantly evolving, one cannot say which strategy will be used and when because these market models analyse forecasts that are a snapshot in time. Therefore, the evolutionary process of T-Evolve* is important as forecast can change over time requiring market models to also change. This is the reason for the feedback loop in Figure 3-2, because as forecasts change so should the beliefs of the users, and this will lead to different formulations of market models to be simulated and the planning process continues again.

Output validation was conducted by comparing the simulated prices with the average real-time prices and actual real-time prices. The results with the average prices showed a similarity as high as 92% in 450745. When compared with actual prices, the similarity was as high as 82% in 533578.

Our findings have significant implications for traders who plan to trade in the real market. Specifically, 1) trading losses may result if forecast beliefs are not accurate especially when markets are volatile, 2) being a buyer or seller can impact profits, so choosing the right position is important, 3) knowing when to be aggressive and when not to be aggressive could impact profits, 4) before trading, a trader should understand who is likely to participate and what their forecast beliefs may be so that counter strategies could be employed, 4) experience may not always lead to more profits.

5.5 Discussion

This section will give an interpretation of the findings from the above analysis. An overview of the results, threats to validity, generalization (where the results are applicable?) and potential impacts on cost, time and quality [Jedlitschka et al., 2008].

5.5.1 Implications of the Results

The results presented above were expected and some unexpected. How do these results relate to earlier research? Table 5-17 below extends the table provided in [Sueyoshi et al., 2008] by adding three more columns and a row for TRAMAS (as shown in Table 2-8). Having the ability to accurately position trades in tomorrow's market can offer an advantage to traders and help to minimize risk of financial loss. The ability to incorporate agent personas is also lacking in all software. Adding agents in the market with different personality types is another aspect of the real market. The culmination of forecast beliefs and personas in a market model is representative of the users' market belief. Most of the technologies fall short on incorporating forecast beliefs and personas in their model. We have showed above that these two factors cannot be ignored for market analysis and can have significant impacts on trading outcomes.

Table 5-17: Comparison between Different Electricity Trading Software

	Estimation	**Transmission**	**Decision Making**	**Analysis**	**Intelligence**	**Incorporates Forecast Beliefs**	**Incorporates Market Beliefs**	**Incorporates Agent Personas**
PowerWeb **[Zimmerman et al., 1999]**	No	No	Yes	Yes	No	No	No	No
Agentbuilder **[Acronymics, 2004]**	No	No	Yes	No	No	No	No	No
SEPIA **[Samad et al., 1996]**	No	No	No	Yes	Yes	No	No	No
MASCEM **[Praca et al., 2003]**	No	No	No	Yes	Yes	No	No	No
EMCAS **[North et al., 2002]**	No	No	Yes	Yes	Yes	No	No	No
MAIS **[Sueyoshi et al., 2008]**	Yes	Yes	Yes	Yes	Yes	No	Yes	No
TRAMAS	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

We can further compare our results to the MAIS model in Table 5-18.

Table 5-18: Similarity comparison between MAIS and TRAMAS[31]

MAIS [Sueyoshi 2010a] vs (PJM Real-time)	MAIS [Sueyoshi 2010a] vs (PJM Day-Ahead)	TRAMAS simulated price vs actual prices	TRAMAS simulated prices vs avg. historical prices
83%	84%	**82%** (533578)	92% (450745)

The results above show a similarity comparison between simulated prices from TRAMAS and simulated prices from MAIS. By looking at the results, it can be seen that TRAMAS and MAIS are similar in their measurements. [Sueyoshi et al., 2010a] shows Day-ahead and Real-Time price comparisons between the simulated prices from MAIS and the actual prices from PJM. If we compare the results, we see that the similarity of TRAMAS is 92% and MAIS is 84% when comparing with PJM Day-ahead prices. And, the MAIS real-time prices comparison is slightly higher at 83% compared to TRAMAS at 82%, which is very similar to what Sueyoshi achieved.

What are the contributions of these results to the underlying theory? There are several areas where TRAMAS contributes to the theory.

1) Decision Support: T-Evolve* developed in this thesis sets the foundation for decision support in trading. It is the first extension of the Evolve* [Ruhe 2004] paradigm to trading. We also introduce PMOs as evolving source of information from agents' actions that users can use for exploration.

2) Validation of Simulation Model: is lacking in the literature. Expert and output validation was conducted. Industry experts were asked to provide feedback on the modeling constructs, and results from TRAMAS. We found that experts were in overwhelming agreement that TRAMAS provides close to "comprehensive coverage" of financial trading. PMO results were empirically validated against actual (observed) prices. PPS analysis was conducted to determine if the simulated price magnitudes and trends were similar to the observed prices and the results confirmed that the simulated prices were similar to the observed prices.

3) Multi-agent simulation: we add actors with certain personas that are instantiated by agents and incorporate forecast beliefs into the agent decision-making process. We show how agents are

[31] The reader is referred to [Sueyoshi et al.,2008, 2010a] on details on their simulation results.

modeled and how incorporation of beliefs creates different outcomes. Each agent, based on its persona, makes decisions that maximize the probability of rewards. The bidding strategies and machine learning capabilities help in the selection of trading strategies. As the results showed, inexperienced agents actually did better that experienced agents in terms of profits generated. Indeed, in trading, there is no set formula or sure bets; in a dynamic market with volatility influenced by many factors, what worked one day may not work the next. The results showed that what one normally expects to generate more profits, might not always be the case.

5.5.2 Threats to Validity

There are several key threats that can affect the validity of the results. These threats can be grouped under three categories: A) threats to construct validity, B) threats to internal validity, and C) threats to external validity.

A) Threats to Construct Validity

It is the degree to which inferences can be made from the operationalization of the model constructs that must be given careful consideration. The types of agents chosen may not represent the types of agents that exist in a particular market. There may be other agent types that could influence market outcomes and this could lead to much different results but not necessarily better. The implication of this on the results is market specific and could vary in its affects in different markets. Other constructs such as modeling experience by adding more noise in the profit equations could also affect results because experience is very difficult to capture. Experience is relative, so ones experience relative to another's experience can be very different. Using a parameter to capture experience must therefore account for relative differences in experiences between others in the market; however, this becomes difficult and not trivial because participants in the market are anonymous.

Furthermore, forecast beliefs play an important role in determining the results but these beliefs are determined by the user, so it becomes important that the user specify these beliefs as accurately as possible otherwise the results may not accurately represent tomorrow's market. However, having the ability and flexibility to model different markets in TRAMAS is also one of its strengths. Lastly, the forecast data used must be carefully chosen for best results. Using data that does not have any influence on the real market will affect the results. Bad data will lead to bad results. Lastly, the bidding strategies also play an important role in helping agents decide by how much to adjust the prices up or down. Choosing unreasonable values for β for the personas could affect the results, because values that are not realistic may lead to unrealistic results. Experts can judge whether the values are reasonable by exploring the results and making refinements to β if the results do not look reasonable.

B) Threats to Internal Validity

The threats to the internal validity of the model must also be considered. Here the data collection process must align with the needs of the market. For example, for the electricity market load and weather forecasts are seen to be important factors in the determination of prices [Pelacci et al., 2001]. The load forecasts are generated by PJM. The data are in hour ending (HE) format ranging from HE1 - HE24. The weather forecasts are from weather.com for the east coast in the USA (United States of America). No manipulations of the data are done to improve the results. The main parameters of the model: α, β, ζ are modifiable by the users through the TRAMAS website (with the exception of ζ, which is a random variable chosen by the system). The implications of choosing wrong data will have negative effects on the results especially if they have nothing to do with the real market; however, choosing different values for the main parameters may or may not have adverse effects on the results because the real market is driven by random factors, and these can change frequently. Therefore, the choice of parameter values is dependent to some degree on the market knowledge of the user. Other processes such as learning uses limited data specific to historical real-time prices, other information for learning could have been incorporated however the implication of this on the bidding strategies would be to make them more complicated which may not necessarily lead to better results. It has been shown in [Sueyoshi et al., 2005] that simpler strategies can lead to good results. Thus the threats to the internal validity of the model are mitigated by making the components of TRAMAS flexible to adjust by the users as they see fit.

C) Threats to External Validity

There is no best market model to help the user determine how tomorrow's market may evolve. What is important is the process of formulating new market models as illustrated by the T-

Evolve* process. This also highlights one of the strengths of TRAMAS: flexibility. Of course with flexibility comes the effort to choose, which may make it difficult for novice users to use TRAMAS. The constructs in TRAMAS are designed to be simple to use and offer results that are easy to interpret; however, the use of experts in interpreting the results to form final trading plans, especially when money is at risk, is always a good idea.

5.5.3 Inferences

Where are the results of TRAMAS applicable? And can they be generalized? The answers to these questions are not easy. For one, the reason TRAMAS was developed as a decision support tool was because of the volatile nature of financial markets. Indeed, if market prediction was possible to a high degree of certainty everyone would be involved in the market with similar predictions and this would reduce market volatility as well as reducing any chance of making money. In addition, market participants are varied and never constant and so the population of users that would benefit from TRAMAS is varied. This is because people's behaviours will change from hour to hour and day to day. This further complicates issues around trade planning and makes the generalization of the results difficult. A market that existed one day may be entirely different another day because many of the drivers of the market are random factors with complex unknown underlying processes. Therefore, we use caution to generalize the results outside of the case studies.

What we can generalize is how TRAMAS approaches trading analysis. Different personas and different forecast beliefs are all present in any market; the only difference is what types are present. For the instantiation to the electricity market, we have chosen certain personas, forecast data and beliefs that we know exist in this market and this was shown to the experts in the survey to see if they agree; and they all unanimously agreed with the model constructs in TRAMAS. However, an extension of the survey to a wider sample should be pursued.

Another aspect of TRAMAS that can be generalized is in the type of market one can analyse. This research chose to analyse the electricity market, we could have easily analysed any other market where trading takes place. The only change that would need to take place is the forecast data and bidding strategies, which could be dependent on the time frequency of the trade.

Specifically, in the electricity market, trades are done on an hourly basis for tomorrow's market, in other markets this may not be the case and trades may happen more in real-time. There may be other changes to the personas of agents.

How scalable is TRAMAS? Can more agents be added, more data, etc. The answer is yes and is only constrained by the computer hardware. Currently, in TRAMAS agents' types can be instantiated to many agents with different beliefs using different estimation methods. More estimation functions can also be added. Thus, TRAMAS is able to scale up with only limitation being the computer hardware.

5.6 Limitations in using TRAMAS

The TRAMAS technology has several additional limitations beyond those already discussed.

Input Uncertainties

Input uncertainties are not considered an issue at the modeling, exploration or consolidation phases. However, to minimize the uncertainties in the quality of the results, existing techniques could be used:

- Group decision-making techniques could be added, such as the Delphi method, to allow for more robust exchange of experiences and knowledge to improve the exploration and consolidation phases. For example, in the exploration phase users could be asked to provide their thoughts on which trades are best or where the opportunities and threats may be in the market. This method could be repeated for each PMO until consensus is reached on the best trades.
- In order to reduce uncertainty during the application of the IDS components the following techniques could help:
    - Hybrid problem solving techniques has the advantage to leverage the strengths of both the computational and human expert intelligence.
    - Evolutionary and iterative approach proposed is a useful framework to build different market models based on expert review of the output data, and using this new knowledge for successive iterations.

- Portfolio of qualified solutions that are selected from a set of solutions that show higher profits and probability of rewards can prove promising in reducing input uncertainties.

It should be noted that while profits and probability of rewards can be used to differentiate among PMOs, it does not imply that these results (profits) will actually materialize in the real market. The results are informational, and should be used in conjunction with other information: TRAMAS cannot be held responsible for trade losses. As well, profits between trade plans does not mean that one plan is more valuable or better than another plan by the amount of the difference in the profits, it may be that for certain personas or strategies another plan may be more appropriate. This is where the evaluation by experts can help to identify qualified plans.

Scalability

The ability for TRAMAS to scale with large amounts of data is only limited by computer hardware and memory. The historical data used by agents contained 5,247 rows of observations up to October 14, 2012[32]. Increasing the data volume could have performance effects in the estimation process such as regression analysis and neural networks. However, since the estimation process is a one-time process, the impacts to the entire process are minimal. Scaling the number of agents will have an impact on computer performance. Specifically, the more agents that are simulated the more computing power that will be needed. The only way to mitigate performance issues is to consider larger memory and hardware requirements.

Quality Requirements

Achieving a certain level of quality in the trade plans is something that is not currently considered and may not be relevant. Because users simulate market models that capture in some sense their beliefs, these beliefs may not be correct and this will be reflected in the results. However, this is exactly the purpose of TRAMAS, to allow users to simulate different market beliefs through the simulation of different market models that may or may not represent the way the market may evolve.

---

[32] See my research website for the raw data: http://people.ucalgary.ca/~smaurice/phd_research_data.xls

TRAMAS Customization

There are many ways that TRAMAS can be customized. Currently, users can modify the β variable that controls the aggressiveness of agents. This customization is done by modifying the code from our website. Other customization is planned for the future where users can make further code changes from a website, such as:

I. Broader access to customizing agents' personas
II. Broader access to customizing learning capabilities of agents
III. Broader access to modifying or writing new queries for analysis of trace data
IV. Stakeholder negotiation

TRAMAS assumes that stakeholders can be brought into consensus on trading decisions. However, this may not be realistic, in cases when stakeholders cannot reach consensus we suggest that the probability of rewards be used to help decide between different trading decisions. Alternatively, the trends of the probability of reward for trades can be used from different PMOs. For example, if one trade is showing an upward trend then this trade should be considered over one showing a downward trend in the probabilities.

The next chapter concludes this thesis. It also presents ideas for future research and directions.

CHAPTER 6: CONCLUSIONS AND FUTURE RESEARCH

6.1 Summary and Contributions

The objective of this thesis was to answer the six research questions (R1-R6), and to validate the model results. In order to achieve this objective we proposed an evolutionary problem solving approach called T-Evolve* for establishing trading plans and developed an intelligent decision support technology called TRAMAS using a multi-agent based simulation approach. We instantiated TRAMAS to the electricity trading domain and showed how T-Evolve* can be applied in this context. The approach and technology comprise the following contributions:

- *Theoretical foundation:* We extend upon an existing Evolve* model for the trading domain and call it T-Evolve* that showed how an iterative approach can be used to make trading decisions: D1-D4. In addition, identifying risks such as when not to buy or sell based on the probability of rewards was also discussed. By enabling users to construct market models that incorporate actors with personas instantiated by agents and forecast beliefs, it can be possible to model tomorrow's market from different perspectives. While not every component of the market is captured – the approach is a start for future additions of different market components. Specifically, different beliefs about who may be in the market, and what their forecast beliefs may be can be simulated to provide important insights into tomorrow's market. We also provide eight (8) findings from the analysis in case study #2. These findings, while within the context of this study, provide interesting insights into trading behaviours of agents with different personas and forecast beliefs. Indeed, personas and forecast beliefs have material impacts on trading behaviours and profits.

- *Process model for trading:* A process model for trading was developed that has the advantage of incorporating forecast beliefs and personas into the bidding strategies for agents. Incorporating learning into the simulation allows agents to formulate bidding strategies that use numerical values to help agents decide which strategy should be used.

- *TRAMAS*: We have developed an IDSS for trading called TRAMAS. What separates TRAMAS from other applications is that it explicitly incorporates forecast beliefs and personas in to the agent model. By simulating market models chosen by users, trace data can be captured and analysed to provide several insights into how tomorrow's market may evolve. As a result of the analysis, an important concept was introduced called potential market outcomes (PMOs). PMOs play an important role in providing the user with information on the market from different perspectives. The evaluation of several PMOs can also help to identify potential opportunities and threats in tomorrow's market to help the user make final trading decisions.

- *Case studies:* We conducted two case studies. The first case study answered the research questions: R1-R3. The results showed overwhelming support from experts on both the modeling constructs and the results from TRAMAS. Specifically, survey responses from a Director, Managers and Sr. analysts all agreed that TRAMAS is a good representation of the actual market. A Cronbach alpha value of 0.848 confirmed that the internal reliability of the test measure was good.

  The second embedded case study answered research questions R4-R6 and validated the simulation output with actual data.

  1. For R4, results showed that the bidding strategies do indeed vary considerably with changes in forecast beliefs and personas. The type of strategies chosen can have significant impacts on profits. Therefore, knowing which strategy to use, or which to not use is an important consideration for trading.
  2. For R5, there was no one condition that affects profits, rather a combination of factors. Specifically, the types of strategies used are important. What position a trader takes, i.e. buying or selling, is also considered important. This highlights the complexity that exists in trading and why it is difficult to analyse.
  3. For R6, we showed that experience does not always pay-off. In fact, it was shown that inexperienced agents actually made more profits than experienced agents. This highlights that what would make rational sense, may not necessarily be true in

trading. It shows that the market may not necessarily reward rational behaviour, within the context of this study.

- We also showed that simulated prices and actual prices were *similar* in both price magnitudes and trends. Comparing our results with other researchers showed similarity in the numbers. Specifically we compared our results to [Sueyoshi 2010a]. Using the PPS measure we were able to show that our generated market cleared price for tomorrow's market over a twenty-hour (24) period were 82% similar with the actual PJM real-time prices in tomorrow's market. Interestingly, when compared to the day-ahead prices TRAMAS is 92% similar compared to 84% from Sueyoshi. What this means is the following:
  1. Two different modeling approaches arrive at similar results; this adds credibility to our method by showing our results are similar to leading researchers in the field.
  2. Our method predicts the day-ahead more accurately (92%) and since traders use the day-ahead prices to establish their bets for tomorrow's market this makes our method more likely to result in better trading plans and potentially more profits.
  3. Our method, as a result of 2, could lead to lesser trading risk of profit loss from bad trades.

The next section discusses how the results address the problems and challenges discussed in Chapter 1.

6.2 Addressing the Challenges

Allowing users to simulate markets before actually participating in the real market has the advantage of potentially removing financial risk while increasing market knowledge. However, several problems and challenges exist that prevent a more structured modeling approach to help provide decision support to traders. This thesis has tackled four of these problems.

First, the lack of a modeling framework makes it difficult to conduct a structured analysis of markets (problem 1). We address this problem by building a flexible framework to analyse a market. We allow users to model markets by choosing different agents types with different personas, different forecast data, different forecast beliefs, and users can also customize code to modify agent parameters (see challenge 1). Adding increased flexibility can also come at a cost.

For example, too much flexibility can confuse the user and make the simulation process more cumbersome. The objective is to try to provide the right level of flexibility without comprising the effectiveness of the application. To ensure the right level of flexibility we employed the model, view and controller (MVC) approach.

Challenge 2 was addressed by simplifying the selection of agents into a drag and drop functionality on the TRAMAS website. An easy to use interface to simplify a complex phenomenon can be difficult. Building an interface that allows a user to quickly navigate to areas in the website for input to start the simulation is an important factor in the usability of the technology. Furthermore, we showed how agents could use different trading strategies based on their personas to make trading decisions. The choice of strategies employed a machine-learning algorithm that used the probability of reward as a driver into the decision-making strategies of agents. The modeling of agents was further refined by separating agents by experience and inexperience. We added more noise to the decision making process of inexperienced traders and no noise to experienced traders. The differences in these two types of behaviours can help to determine how the market may evolve with more inexperienced traders than experienced traders or vice versa.

Direction on modeling agents' personas has been lacking in the literature (problem 2). We showed how four personas: experienced aggressive, inexperienced aggressive, experienced non-aggressive and inexperienced non-aggressive can be modeled. These different personas when modeled in a market give rise to market dynamics that make the prediction of market variables, like prices, difficult. Adding to this difficulty is the strategic behaviour of different types of agents that result in opportunistic and risk taking behaviours that adds to the market volatility. We show how different personas are model by using parameters to modify the aggressiveness and experience levels of agents (see challenge 3).

The influence on behaviours is never a straightforward or linear occurrence. Many factors can influence behaviour from type of weather to gut feelings. Finding a systematic way to model behaviour can be complicated and never perfect but it can lend insights into how behaviour changes can influence the bidding behaviours of agents. Put another way, relations between variables that hold at one time, may not always hold in other times. This leads to the problem of how to provide decision support to traders (see problem 3). T-Evolve* incorporates the human and computational intelligence to provide decision support to traders (see challenge 4).

The analysis of the results from trace data is another important aspect of TRAMAS, but data mining agents' actions is lacking (see problem 4). To make the analysis interesting we ask a simple question in this thesis that the research ignores (see challenge 5). Market forecasts will not always be correct; in fact, many times there will be errors in the forecast. These errors can have impacts if the forecast is used to make price predictions. This thesis shows how forecast beliefs can have an impact on the way the market evolves. In particular, we show how forecast beliefs can be mathematically modeled into agents' behaviours. Most of the forecasts are publicly available, if all agents use the same forecasts then their view on how the market may evolve may be similar, but if the real market does not evolve as the forecast suggests and if a trader were to build this into his belief model it could present a possible advantage for him. In the future enhancement of TRAMAS a user can simulate different forecast belief and view their impacts; using the analysis component to mine the data for intelligence could offer further insights into tomorrow's market.

While the simulated results were close to the actual results, were they meaningful? The results were meaningfulness in the author's view but this is a somewhat biased view, to add credibility to the results experts in industry were surveyed to evaluate the constructs and provide their feedback. The result was an objective analysis of the TRAMAS model that should give readers further confidence that the simulation results are a reasonable representation of what may happen in the real world. Similarity analysis also provided support for TRAMAS. The next section discusses TRAMAS from a decision support perspective.

6.3 Effort versus Benefit

There is risk in the financial market because it is constantly evolving. Due to this risk of constant change, market participants face increasing market uncertainties that affect the types of decisions they make. Not participating in the market is an option to eliminate the risk, but this also eliminates any reward from participating in the market. It is because of the potential for rewards that causes users to participate in the market and trade. However, if it is your job to trade and you are responsible for your company's assets, then your losses are the company's losses. The wide web of financial markets impacts almost everyone today, therefore, these losses tend to affect others through this web in some indirect way.

Traders will find TRAMAS a useful technology just for the fact that it allows users to gain insights into tomorrow's market. This information can be used to make trading decisions. Therefore, if the effort is minimal to run TRAMAS, yet the information it can provide helps to provide market insights, with potential for rewards, then the benefits outweigh the effort. We validate this as follows:

1. In case study #1

   a) We showed that experts overwhelmingly found that the modeling constructs in TRAMAS and its results provided comprehensive coverage.

   b) We asked experts whether they would use TRAMAS in an actual market, majority of the experts were very confident in using TRAMAS in an actual market.

   c) We received no negative comments from experts about TRAMAS; the majority of comments were all positive.

Based on the expert feedback for this sample, TRAMAS was beneficial.

2. TRAMAS was able to help choose trades that are likely to provide rewards. Using a systematic approach to determine trades is better than an ad hoc approach [Du et al., 2006]. This means that there could be an effort savings as ad hoc trades increase the chance of losses, which will require a search for more information to reduce losses in subsequent trades. In fact, the trade suggestions from TRAMAS were tested with real data and it was shown that TRAMAS predicted the direction in the real market 77% of the time. Specifically, we found that had a trader used the trade suggestions from TRAMAS he would more likely won than lost.

3. Running the simulation involves dragging and dropping market components, choosing parameters and hitting the "Run Simulation" button. The analysis of the trace data can provide quick information and market insights.

6.4 Future Research

There are several areas where additional research could further investigate the results from TRAMAS or evolve the body of knowledge by maturing the work done in this thesis. Future research could include the following:

- Different personas can be modeled in TRAMAS other than the four types identified. Different personas could help to see how market prices evolve as different agents exist in the market. Currently, in each simulation, personas remain constant throughout the simulation; future research can look at changing agent personas during the simulation. Changing personas during a simulation could be dependent on factors that force agents to change in an effort to maximize profits or minimize losses. For example, during a certain time of the day an agent could be less aggressive and more aggressive during peak hours in the day. Alternatively, an agent could be less aggressive on weekends and more aggressive in the weekdays, etc. This area would answer the research question: How do the changes in personas during the simulation influence prices for buyers and sellers?

- Incorporating a game theoretic approach could increase the strategic nature of agents. As discussed in section 1.8 one way this could be done is to incorporate the β value of different agents into other agents to see if this affects the profits generated. For example, it could be that non-aggressive agent's trade less if they feel aggressive traders are in the market. If this is the case, then aggressive agents should make more profits? Or non-aggressive agents may only trade specific hours that are less volatile such as off-peak hours. Behaviours like this could have different effects on the market price which could influence the final trade plan chosen by the user.

- Another area of future research would be to compare the results of TRAMAS with other electricity trading software. The comparison could be based on which technology generates the most profits. This head-head competition could be important to either further validate the TRAMAS technology or point to areas where TRAMAS can be further improved. Such improvements may be to identify optimal trading behaviour from different simulations.

- Additional (forecast) data could be used for agents to make their predictions. For the electricity market, we used load and weather forecast data, which are two main data sources fundamentally affecting electricity prices, but adding additional data that could have an impact on prices could be added. For example, adding electricity grid information such as forecasted plant outage information could help agents form better decisions about tomorrow's prices. This could answer the research question: Do impacts of plant outages affect market price outcomes for buyers and sellers with different forecast beliefs and personas?

- Bidding strategies are also an interesting area for further research. One way to implement bidding strategies was shown. However, more complicated strategies based on different trading scenarios could be devised to help agents bid more strategically as discussed in section 2.6. For example, while learning is an important concept, strategies could incorporate a game theoretic approach that takes into consideration the possible actions of other market participants; these actions could be simple or very complicated. This could answer the research question: How does incorporating the actions of other agents influence the market prices for buyers and sellers with different forecast beliefs and personas?

- Additional decision variables could be explored. Currently, we use α, β, and ζ as the forecast beliefs, price discount or markup, and experience parameters, respectively, for the simulations. Additional decision parameters could be added that make up a risk score, which would determine if the agent trades or not; if it trades, how aggressive or non-aggressive will it be. A risk score would effectively capture the risks from all other factors and could help the agent make better decisions about the future market outcome. This could answer the research question: What is the impact of using a risk score on profits for buyers and sellers with different forecast beliefs and personas?

- Additional market models with more variations in the events and agents will be done. By having a wider set of different market models with more agents could provide more variations in the results and lead to more diversification in the trade plans, this could impact the profits and probability of rewards in the plans.

- The survey could be extended to a wider range of experts. Having more evaluations of TRAMAS by more people could help to provide a more accurate picture on whether TRAMAS is a useful technology for the real market.

6.5 **Future Research Directions**

From the literature review, it was evident that there is no standard or systematic way to analyze a financial market or determine how a future market may evolve. Methods are diverse without any consensus on the modeling constructs or artifacts. Possible future work that could improve DSS using agent-based simulation methods are:

- Validation of simulation models. Only few guidelines have been defined to validate agent-based simulation models [Weidlich, et al., 2008]. This brings us to an open research issue:

    Q1: To find systematic ways to validate simulation models, specific to trading.

Possible directions that could help address Q1 is given in [Weidlich, et al., 2008], who critically review large amount of research in the area of agent based technologies and the different validation techniques used. This is a good starting point to understand the current techniques and establish commonalities and differences that could lead to a more systematic method of validation.

- Another issue is how to use agent based approaches to test market rules. Specifically, what human behaviours could stress or violate market rules and under what conditions are rules likely to be violated. This leads to the second issue:

    Q2: To provide a robust agent based simulation to stress test market rules.

Human based testers are expensive and take time to train. [Thomas and Mount 2005] show how an agent-based approach can help to test electric markets and system.

- How to advance agent learning capabilities such that they can adapt to changing circumstance quickly and respond accurately within a trading context and how this can be scaled with large amount of agents and data, remains a challenge. The issue is

    Q3: To advance agent-learning capabilities in a fast paced, constant change environment with large amounts of data.

Some direction on how to address this issue can be found in [Weidlich, et al., 2008]. This research proposed an agent learning approach for different personas that could be extended to deal with more real-time environments.

- Different way to provide decision support to traders is another open issue. This research has proposed one way to provide support. This leads us to the last open issue:
  - **Q4:** To find more effective ways to provide intelligent decision support to traders, with validation.

A starting point to address this issue can be found in [Lim & Jain 2010]. These authors provide an overview of intelligent decision support systems and provide taxonomy of decision support systems. Actual traders should do validation because only then can one determine how the system can perform in the real world.

REFERENCES

1. Abidin, S. and M. M. Jaffar (2012), "A Review of Geometric Brownian Motion in Forecasting the Share Prices in Bursa Malaysia", World Applied Sciences Journal 17, 87-93.

2. Acronymics, I. (2004), Agentbuilder 1.4, Acronymics, Inc., 2004.

3. Alter, S. (2004), “A work system view of DSS in its fourth decade”, Decision Support Systems 38, pp. 319-327.

4. Arnott, D., and P. Graham (2008), “Eight key issues for the decision support systems discipline”, Decision Support Systems 44, pp. 657-672.

5. Baqueiro, O., J. Yanbo, P. Wang, P. McBurney, and F. Coenen (2009), “Integrating Data Mining and Agent Based Modeling and Simulation”, Computer Science Advances in Data Mining. Applications and Theoretical Aspects Lecture Notes in Computer Science 25633/2009, pp. 220-231.

6. Bass, L., P. Clements, and R. Kazman (1998), Software Architecture in Practice. Addison-Wesley (Boston, Massachusetts).

7. Bekiros, S.D. (2010), "Heterogeneous trading strategies with adaptive fuzzy Actor–Critic Reinforcement learning: A behavioral approach", Journal of Economic Dynamics & Control 34, 1153–1170.

8. Benos, A. V. (1998), "Aggressiveness and survival of overconfident traders", Journal of Financial Markets 1, 353-383.

9. Black, F. and M. Scholes (1973), "The pricing of options and corporate liabilities", Journal of Political Economy, (81), pp.637-654.

10. Booch, G. (1994), Object-Oriented Design with Applications. Benjamin/Cummings (Redwood City, CA).

11. Booch, G., I. Jacobson, and J. Rumbaugh (1998), The Unified Modeling Language User Guide. Addison-Wesley (Boston, Massachusetts).

12. Bouyssou, D., T. Marchant, M. Pirlot, P. Perny, A. Tsoukiàs, Ph. Vincke (2000), “Evaluation and Decision Models: A Critical Perspective”, Kluwer Academic, Dordrecht.

13. Buchanan, M. (2009), “Meltdown Modeling”, Nature 460(6), pp. 680-682.

14. Bunn, D.W., and F. S. Oliveira (2001), “Agent-based simulation an application to the new electricity trading arrangements of England and Wales”, IEEE Transactions on Evolutionary Computation 5(5), pp. 493-503.

15. Carvalho, J.P. and J.A.B. Tome (1999), "Rule based fuzzy cognitive maps and fuzzy cognitive maps-a comparative study", Fuzzy Information Processing Society, 1999. NAFIPS. 18th International Conference of the North American.

16. Chandarasupsang, T., S. Galloway, G. Burt, J. McDonald, and T. Siewierski (2004), “Bidding behaviour and electricity market simulation”, International Conference on Probabilistic Methods Applied to Power Systems, 2004 (Iowa State University, Ames), pp. 349-355.

17. Chang, S-C., S.-S. Chen, K. R. Chou, and Y.-H. Lin (2008), "Weather and intraday patterns in stock returns and trading activity", Journal of Banking & Finance 32, pp. 1754–1766.

18. Chen-Ching, L. (2001), “Decision support tools for trading in deregulated energy systems”, Power Engineering Society Summer Meeting, 2001 (Vancouver, BC), pp. 409-410.

19. Chiam, S.C., K.C. Tan, A. Al Mamun (2009), "Investigating technical trading strategy via an multi-objective evolutionary platform", Expert Systems with Applications 36, 10408–10423.

20. Cronbach, L. J. (1951), “Coefficient alpha and internal structure of tests”, Psychometrika 16(2), pp. 297-334.

21. Davidsson, P., J. Holmgren, H. Kyhlbäck, and D. Mengistu (2007), “Applications of Agent Based Simulation”, Multi-Agent-Based Simulation VII Lecture Notes in Computer Science 4442, pp.15-27.

22. DeGregorio, G. (1999), “Enterprise-wide Requirements and Decision Management”, Proc. Int'l Symp. Int'l Council on Sys. Eng., 1999 (Brighton, England).

23. Denzinger, J., and J. Hamdan (2004), “Improving Modeling of other Agents using Tentative Personas and Compactification of Observations”, Proc. IAT, 2004 (Beijing, China), pp. 106-112.

24. Denzinger, J., and G. Ruhe (2004), “Decision Support for Software Release Planning Using e-Assistants”, Journal of Decision Support Systems 13(4), pp. 399-421.

25. Dey, E. L. (1997), "Working with Low Survey Response Rates: The Efficacy of Weighting Adjustments", Research in Higher Education 38(2), pp. 215-227.

26. Du, G., J. McElroy, and G. Ruhe (2006), “Ad hoc versus Systematic Planning of Software Releases – A Three Staged Experiment,” in 7th International Conference on Product Focused Software Process Improvement (PROFES06), Amsterdam.

27. Fahlenbrach, R. and Sandas, P. (2010), "Does information drive trading in option strategies?", Journal of Banking & Finance 34(10), 2370-2385.

28. Fama, E. (1970), “Efficient capital markets: a review of theory and empirical work”, Journal of Finance 25(2), pp. 383-423.

29. Farmer, D. J., and D. Foley (2009), “The economy needs agent-based modeling”, Nature 460(6), pp. 685-686.

30. FERC (Federal Energy Regulatory Commission) (2012), Energy Primer: A Handbook of Energy Market Basics, A staff report of The Division of Energy Market Oversight, Office of Enforement. http://www.ferc.gov/market-oversight/guide/energy-primer.pdf

31. Fenton, S. (2001), “Conducting and Presenting Empirical Software Engineering”, Empirical Software Engineering 6, pp. 195-200.

32. Franci, F., R. Marschinski, and L. Matassini (2001), "Learning the optimal trading strategy", Physica A 294, pp. 213–225.

33. Frankfurter, G. M. (2006), “The Theory of Fair Markets (TFM) toward a new finance paradigm”, International Review of Financial Analysis 15, pp. 130–144.

34. Fudenberg, D., and C. Harris (1992), “Evolutionary Dynamics with Aggregate Shocks”, Journal of Economic Theory 57 (2), 420–441.

35. George, D., and P. Mallery (2003), SPSS for Windows step by step: A simple guide and reference. 11.0 update (4th ed.). Allyn & Bacon (Boston, Mass.).

36. Gode, D. K., and S. Sunder (1993), “Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality”, The Journal of Political Economy 101(1), pp. 119-137.

37. Gottinger, H. W., and P. Weimann (1992), “Intelligent decision support systems”, Decision Support Systems 8, pp. 317-332.

38. Gujarati, D. (1988), Basic Econometrics, Second edition. McGraw–Hill (New York).

39. Haefke, C., and C. Helmenstein (2000), “Predicting stock market averages to enhance profitable trading strategies”, Proceedings of the Third International Conference on Neural Networks in the Capital Markets, 2000 (London, England), pp. 378–389.

40. Helbing, D. and S. Balietti (2012), "How to Do Agent-Based Simulations in the Future: From Modeling Social Mechanisms to Emergent Phenomena and Interactive Systems Design”. In D. Helbing, Social Self-Organization, Understanding Complex Systems. Springer-Verlag: Berlin Heidelberg.

41. Hongtao, Z., J. Jiang, W. Zeng, G. Liu, and Y. Wang (2010), “Simulation experiment of continuous double auction stock market based on multi-agent model”, International Conference on Progress in Informatics and Computing (PIC), 2010 (Shanghai, China), pp.5-9.

42. Huang, W., H. Zheng, and W.-M. Chia (2010), "Financial crises and interacting heterogeneous agents", Journal of Economic Dynamics & Control 34, pp. 1105–1122.

43. Izumi, K., F. Toriumi, H. Matsui (2009), "Evaluation of automated-trading strategies using an artificial market", Neurocomputing 72, 3469–3476.

44. Java BluePrints, Model-View-Controller (2003) http://java.sun.com/blueprints/patterns/MVC-detailed.html.

45. Jeffrey, R., and L. Scott (2002), “Has twenty five years of empirical software engineering made a difference”, Proc. Asia–Pacific Softw. Eng. Conf., 2002 (Queensland, Australia), pp. 539-546.

46. Kandori, M., R. Serrano, and O. Volij (2008), "Decentralized trade, random utility and the evolution of social welfare", Journal of Economic Theory, Elsevier, vol. 140(1), pages 328-338, May.

47. Karlstrom, D., and P. Runeson (2006), “Integrating agile software development into stage-gate managed product development”, Empirical Software Engineering 11, 203-225.

48. Kian, A. R., and J. B. Cruz, Jr. (2005), “Bidding strategies in dynamic electricity markets”, Decision Support Systems 40(3), pp. 543-551.

49. Kidney, J., and J. Denzinger (2006), “Testing the Limits of Emergent Behavior in MAS Using Learning of Cooperative Behavior”, Proceedings of the 17th European Conference on Artificial Intelligence, ECAI 2006 (Trentino, Italy), pp. 260-264.

50. Kitchenham, B., and S. L. Pfleeger (2002), "Principles of Survey Research Part 2: Designing a Survey", Software Engineering Notes, 27(1), pp.18-20.

51. Kitchenham, B., and S. L. Pfleeger (2003), "Principles of Survey Research Part 6: Data Analysis", Software Engineering Notes 28(2), pp. 24-27.

52. Kitchenham, B. (2004), “Procedures for Undertaking Systematic Reviews”, Joint Technical Report, Computer Science Department, Keele University (TR/SE- 0401) and National ICT Australia Ltd.

53. Kitchenham, B., O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman (2009), "Systematic literature reviews in software engineering – A systematic literature review", Information and Software Technology 51, pp. 7–15.

54. Kozhan, R., and W. Schmid (2009), "Asset allocation with distorted beliefs and transaction costs", European Journal of Operational Research 194, pp. 236–249.

55. Kung, C.H., and A. Solvberg (1986), "Activity Modeling and Behavior Modeling", In: T. Ollie, H. Sol, A. Verrjin-Stuart, Proceedings of the IFIP WG 8.1 working conference on comparative review of information systems design methodologies: improving the practice. North-Holland, Amsterdam (1986), pp. 145-171.

56. Lim, C. P., and L. C. Jain (2010), "Advances in Intelligent Decision Making", Handbook on Decision Making Intelligent Systems Reference Library 4(I), pp. 3-28.

57. Macal, C. M. (2005), "Model Verification and Validation", Workshop on"Threat Anticipation: Social Science Methods and Models", The University of Chicago and Argonne National Laboratory, April 7-9, Chicago, IL.

58. Macal, C. M., and M. J. North (2007), "Agent-based modeling and simulation: Desktop ABMS", Proceedings of the 2007 Winter Simulation Conference S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, eds., 2007 (Washington, DC), pp. 95-106.

59. Maenhoudt, M., and G. Deconinck (2010), "Agent-based modelling as a tool for testing electric power market designs", 7th International Conference on the European Energy Market (EEM), 2010 (Madrid, SPAIN), pp. 1-5.

60. Maes, P., R. H. Guttman, and A. G. Moukas (1999), "Agents that buy and sell", Communications of the ACM 42(3), pp. 81-91.

61. Marks, R. E. (2007), "Validating simulation Models: A general framework and four applied examples", Computational Economics 30(3), pp. 265-290.

62. Maurice, S., G. Ruhe, O. Saliu, and A. Ngo-The (2005), "Decision Support for Value-Based Software Release Planning". In S. Biffl, A. Aurum, B. Boehm, H. Erdogmus, P. Grünbacher (Eds.), Value-Based Software Engineering, Springer (New York), pp. 247-261.

63. Mayall, M. (2009), "A feeling for finance: Motivations for trading on the stock exchange", Emotion, Space and Society 19(1), pp. 1–8.

64. Mohebzada, J., G. Ruhe, and A. Eberlein (2012), "Systematic Mapping of Recommendation Systems for Requirements Engineering", International Conference on Software and Systems Process (ICSSP), Zurich, Switzerland.

65. Naylor, T. H., and J. M. Finger (1967), "Verification of Computer Simulation Models", Management Science 14(2) pp. 92-106.

66. Nikolaidou, V., and P. A. Mitkas (2009), “A Sequence Mining Method to Predict the Bidding Strategy of Trading Agents”, Agents and Data Mining Interaction Lecture Notes in Computer Science 5680/2009, pp. 139-151.

67. North, M., G. Conzelmann, V. Koritarov, C. Macal, P. Thimmapuram, and T. Veselka (2002), “E-laboratories: agent-based modeling of electricity markets”, Proceedings of the 2002 American Power Conference, 2002 (Chicago, IL).

68. Pěchouček, M., and V. Mařík (2008), “Industrial deployment of multi-agent technologies: review and selected case studies”, Autonomous Agents and Multi-Agent Systems 17(3), pp. 397-431.

69. Pfleeger, S. (2002), “Making Good Decisions: Software Development and Maintenance Projects”, Tutorial at 8th IEEE Symposium on Software Metrics, 2002 (Ottawa, Canada).

70. Power, D., and R. Sharda (2007), "Model-driven decision support systems: Concepts and research directions", Decision Support Systems 43, pp. 1044– 1061.

71. Praca, I., C. Ramos, Z. A. Vale, and M. Cordeiro (2003), “MASCEM: a multiagent system that simulates competitive electricity markets”, Intelligent Systems 18(6), pp. 54-60.

72. Qian, Zhang, and J.-H. Yu (2006), “Bidding Decision-Making Support System for Power Supplier Based on Multi-Agent System”, International Conference on Power System Technology, PowerCon 2006 (Chongqing, China), pp.1-6.

73. Raberto, M., S. Cincotti, S. Focardi, and M. Marchesi (2001), “Agent-based simulation of a financial market”, Physica A 299, pp. 319-327.

74. Rittel, H., and M. Webber (1973), "Dilemmas in a general theory of planning," Policy Sciences 4, pp. 155-169.

75. Robson, C. (2002), Real World Research. Blackwell (Boston, MA).

76. Ruhe, G. (2004), “Software Engineering Decision Support and Empirical Investigations - A Proposed Marriage”, Empirical Studies in Software Engineering 2, pp. 25-34.

77. Ruhe, G. (2010), Product Release Planning: Methods, Tools and Applications, CRC Press.

78. Runeson, P., and M. Höst (2009), "Guidelines for conducting and reporting case study research in software engineering", Empirical Software Engineering 14(2), pp. 131–164.

79. Samad, T., S.A. Harp (1996), SEPIA 1. Honeywell Technology Center.

80. Sargent, R. G. (1998), “Verification and Validation of Simulation Models”, Proceedings of the Winter Simulation Conference, eds: D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan, pp. 124-137.

81. Sevastianov, P., and L. Dymova (2009), “Synthesis of fuzzy logic and Dempster-Shafer Theory for the simulation of the decision-making process in stock trading systems”, Mathematics and Computers in Simulation 80(3), pp.21-30.

82. Shannon, R. E. (1977), “Simulation modeling and methodology”, ACM SIGSIM Simulation Digest 8(3), pp. 33–38.

83. Shaw, M. (2003), "Writing Good Software Engineering Research Papers: Minitutorial", Proceedings of the 25th International Conference on Software Engineering, IEEE Computer Society, pp. 726-736.

84. Singh, R., and H. S. Sarjoughian (2003), “Software Architecture for Object-Oriented Simulation Modeling and Simulation Environments: Case Study and Approach”, Technical Report TR-03-09.

85. Stol, K.-J., and B. Fitzgerald (2013), "Uncovering Theories in Software Engineering", GTSE 2013, San Francisco CA, USA.

86. Sueyoshi, T., and G. R. Tadiparthi (2005), “A Wholesale Power Trading Simulator with Learning Capabilities”, IEEE Transactions on Power Systems 20(3), pp.1330–1340.

87. Sueyoshi, T., and G. R. Tadiparthi (2007), “Why did California electricity crisis occur? A view of multi-agent intelligent simulator”, IEEE International Engineering Management Conference, 2007 (Austin, TX), pp. 36-41.

88. Sueyoshi, T., and G. R. Tadiparthi (2008), “An agent-based decision support system for wholesale electricity market”, Decision Support Systems 44(2), pp. 425-446.

89. Sueyoshi, T., M. Goto (2010a), “Multi-Agent Intelligent Simulator to estimate U.S. wholesale price of electricity”, International Conference on Systems Man and Cybernetics (SMC), 2010a (Istanbul, Turkey), pp. 3278-3283.

90. Sueyoshi, T. (2010b), “A Use of Multi-Agent Intelligent Simulator to Measure the Dynamics of US Wholesale Power Trade: A Case Study of the California Electricity Crisis”, Innovations in Multi-Agent Systems and Applications - Studies in Computational Intelligence 310, pp. 69-111.

91. Sueyoshi, T. (2010c), “An agent-based approach with collaboration among agents: Estimation of wholesale electricity price on PJM and artificial data generated by a mean reverting model”, Energy Economics 32(5), pp. 1025–1033.

92. Szakmary, A. C., Q. Shen, S. C. Sharma (2010), "Trend-following trading strategies in commodity futures: A re-examination", Journal of Banking & Finance 34, 409–426.

93. Teive, R.C.G., V. do Itajai, T. Lange, G.A.B Arfux, A.K. Queiroz, L.F.S.C. Rosa, and A.V. Neto (2010), “A decision support system for energy trading and portfolio optimization”, 7th International Conference on the European Energy Market (EEM).

94. Thomas, R.J., and T.D. Mount (2005), “Using software agents to test electric markets and systems”, IEEE Power Engineering Society General Meeting 3, pp. 2808-2812.

95. Trigo, P. M., and H. C. (2009), “TEMMAS: The Electricity Market Multi-Agent Simulator”, Bio-Inspired Systems: Computational and Ambient Intelligence Lecture Notes in Computer Science 5517, pp. 569-576.

96. van den Bergh, W.M., K. Boer, A. de Bruin, U. Kaymak, and J. Spronk (2001) "On Intelligent-Agent Based Analysis of Financial Markets", 29th meeting of EURO Working Group on Financial Modelling.

97. Vriend, N. (2003), “’From Exchange It Comes to Tears’. A Dutch ‘Folk Theorem’ Reconsidered”, Theory and Decision 55, pp. 315–338.

98. Walter, I., and F. Gomide (2008), “Electricity market simulation: multiagent system approach”, Proceedings of the ACM symposium on Applied computing ACM, SAC '08 (New York).

99. Wang, J.-H., K. S.-M. Chen, and J.-Y. Leu (1997), “Stock trading decision support system using a rule selector based on sliding window”, International Conference on Computational Cybernetics and Simulation, 1997 (Orlando, FL), pp. 559-564.

100. Wang, Y. (2008), "Toward a Generic Mathematical Model of Abstract Game Theories", Trans. on Comput. Sci. II, LNCS 5150, 205-223.

101. Wang, Y. and G. Ruhe (2007), “The Cognitive Process of Decision Making”, Int’l Journal of Cognitive Informatics and Natural Intelligence, 1(2), pp. 73-85.

102. Weidlich, A., and D. Veit (2008), “A critical survey of agent-based wholesale electricity market models”, Energy Economics 30(4), pp. 1728–1759.

103. Wen, F.S, and A.K. David (2001), “Strategic bidding for electricity supply in a day-ahead energy market”, Electric Power Systems Research 59(3), pp. 197–206.

104. Wooldridge, M., and N.R. Jennings (1995), “Intelligent Agents: Theory and Practice,” The Knowledge Engineering Review 10(2), pp. 115-152.

105. Zimmerman, R., R. Thomas, D. Gan, and C. Sanchez (1999), “A web-based platform for experimental investigation of electric power auctions”, Decision Support Systems 24 (3–4), pp. 193–205.

Appendix A **Ethics Application File**

This appendix shows the actual ethics application form approved by the Conjoint Faculties Research Ethics Board (CFREB).

<table>
<tr><td colspan="2">1.1 Applicant:</td></tr>
<tr><td>Family Name
Maurice</td><td>Given Name and Initial
Sebastian Augustine</td></tr>
<tr><td colspan="2">Department/Faculty
Electrical and Computer Engineering</td></tr>
<tr><td rowspan="2">Mailing Address (complete only if different from Department/Faculty)
13 Wentworth Heath S.W.
Calgary, Alberta
T3H 5V2</td><td>E-mail Address
Sebastian.maurice@gmail.com
smaurice@ucalgary.ca</td></tr>
<tr><td>Telephone (local)
403-828-9431</td></tr>
<tr><td colspan="2">Title/Position (Check One)
[ ] Full-time Faculty Member
[ ] Adjunct Faculty Member
[ ] Postdoctoral Fellow
[ ] Sessional Instructor
[ ] Professor Emeritus
[ ] Staff Member
[x] Graduate Student: [ ] Master's [x] Ph. D [ ] Other (please specify):
[ ] Undergraduate Student
[ ] Other (please specify):</td></tr>
<tr><td colspan="2">1.2 Supervisor, if applicable:</td></tr>
<tr><td>Family Name
Ruhe</td><td>Given Name and Initial
Guenther</td></tr>
<tr><td colspan="2">Department/Faculty
Electrical and Computer Engineering</td></tr>
<tr><td rowspan="2">Mailing Address (complete only if different from Department/Faculty)</td><td>E-mail Address
ruhe@ucalgary.ca</td></tr>
<tr><td>Telephone (local)
403-220-7692</td></tr>
<tr><td colspan="2">Title/Position (Check One)
[x] Full-time Faculty Member
[ ] Adjunct Faculty Member
[ ] Sessional Instructor
[ ] Professor Emeritus
[ ] Other (please specify):</td></tr>
<tr><td colspan="2">1.3 Co-Applicant, if applicable:</td></tr>
</table>

Family Name	Given Name and Initial
Department/Faculty	
Mailing Address (complete only if different from Department/Faculty)	E-mail Address Telephone (local)

Title/Position (Check One)
[ ] Full-time Faculty Member
[ ] Adjunct Faculty Member
[ ] Postdoctoral Fellow
[ ] Staff Member
[ ] Sessional Instructor
[ ] Professor Emeritus
[ ] Graduate Student: [ ] Master's [ ] Ph. D [ ] Other (please specify):
[ ] Undergraduate Student
[ ] Other (please specify):

1.4 Additional Research Team Members: Provide as an attachment.
If other person or persons is/are involved in the project, but not affiliated with the University of Calgary, please provide his or her name, organization/employer, affiliation and other details to identify them.

2. Project Details:

2.1 Exact Title of the Project
Intelligent Decision Support System for Trading

2.2 Is this an amendment/modification to a previously approved protocol? [x] No [ ] Yes (Note: see Information to Help Applicants for more details. Separate procedures apply when modifications do not involve significant changes to the original protocol. Please contact the CFREB office [220-3782] if you are unsure whether the changes to an existing protocol constitute a modification/amendment, or are significant enough to warrant a new application.)

2.3 Status of funding/support for the project - please choose one:
[x] Unfunded project [ ] Funding pending [ ] Funding received
Sponsor(s)/funding agency(s): [ ] SSHRC [ ] NSERC [ ] CIHR Other (please specify):

Name of investigator(s) applying for or receiving funding:
Project title as submitted to funding agency (if different than title of ethics submission):

2.4 Anticipated start date of work involving human participants (mm/yy) **05/2012**	Anticipated completion date of research activity; for graduate thesis or dissertation, please list anticipated date of defense (mm/yy) 12/2012

2.5 List the location(s) where the data will be collected http://www.think2advance.com/tramas/phdlogin.php - this is the main website users will log in to and is under the full control by the applicant. After the users have submitted their results, they can retrieve a http://www.think2advance.com/tramas/phdlogin.php?username=[username], where [username] is the username assigned to the user by the applicant.
2.6 Are other approvals/permissions required where this research will occur? [x] No [ ] Yes If yes, provide a copy of the approval: [ ] Attached [ ] To follow (Specify where from): 4.4

2.7 Provide a succinct summary of the purpose, objectives, and aims of the research. Describe your methodology, and what will be required of the human participants. Please use language that can be understood by a non-specialist. Up to 1 additional page may be added, if required. (Note: Project descriptions exceeding the two-page limit will not be considered.) **REMINDER:** Be sure to include a copy of any questionnaire(s) or test instrument(s).

Project Summary:

We argue that a focus of trading research should be on modeling and educating traders; to help them to learn electricity market fundamentals so they can confidently trade in the real market. We pose the following research question:

R1) Does observing the behaviors and interactions of different actors, coupled with an intelligent decision support system (IDSS), increase the confidence in users' knowledge to trade in the real market, under specific usage scenarios?

Each survey question is designed to help answer the above research question by asking users pre-survey questions. These pre-survey questions capture the respondents confidence in their knowledge of the electricity market. Then users are asked to view the simulation results from TRAMAS that highlight specific scenarios (explained below), that will show the changes in prices with changes in load forecasts in an agent based simulation. Then users are asked a post-survey questionnaire. The type of measurement is how users confidence in their knowledge has changed after seeing the TRAMAS results. Statistically we test two hypotheses (H0 and H1) below using one-tailed T-Statistic and confidence interval:

H0: change in users' confidence in their knowledge of the market is 0 (Change=0)

H1: change in users' confidence in their knowledge of the market is greater than 0 (Change>0)

Specifically the T-statistic is computed by using the mean difference between the pre and post responses divided by the standard error of the mean difference. If this T-statistic is greater than the critical T-value at a particular level of significance (5% or 10%) then we can reject H0 for H1, otherwise H0 cannot be rejected. By not rejecting H1, we will have shown that within our sample, the confidence has increased, but unfortunately cannot show by how much, rather we can give a confidence interval of the mean difference of the change; this approach will address R1.

Methodology:

There are two parts to this study:

1) Face validity by experts familiar with the electricity market.

Experts are chosen using three criteria: professionally works in the electricity industry and has over 5 year years of experience in this industry. The aim is to get 7-10 experts who meet the above criteria. Most experts will be recruited from major electricity organizations. Presently three experts come from Genscape Corporation (http://www.genscape.com/), Energy Central (http://www.energycentral.com/), ENMAX Corporation (http://www.enmax.com/)

2) Survey of participants

<u>For 1) :</u> Experts will be asked to look at the causal model, model assumptions, model components, and model results and provide their feedback. Specifically they will answer the following:

a) What is your Expert Judgement of TRAMAS' Model Components?

b) What is your Expert Judgement of TRAMAS' Model Assumptions?

c) What is your Expert Judgement of TRAMAS' Process Model?

d) Based on your experience, are the concepts and modeling approach (agents with personality types, decision support, agent simulation and post analysis of agent interactions), new and effective for training traders? Please explain why or why not?

1.2): Experts will be asked to look at the model results on a website and provide their feedback. Specifically they will answer the following for:

a) Question 1: Looking at Chart 1. How well has TRAMAS represented the PRICES for the actual virtual real-time PJM market?

b) Question 2: Looking at Chart 1. How well has TRAMAS represented the PRICE TRENDS for the actual virtual real-time PJM market?

c) Question 3: Looking at the results in Tables 1-9. How well has TRAMAS represented an ACTUAL day-ahead and virtual real-time PJM market?

d) Question 4: From a scale from 1 to 5 where 1 is not very confident and 5 is very confident. How confident would you be to use TRAMAS (in different simulations) to help you trade in the REAL PJM market?

For 2): Users will be asked to answer a pre-survey questionnaire of their knowledge of the electricity market. Then the users will be asked to review results from the simulation. The users will view TWO result sets: (result sets can be found here http://www.think2advance.com/tramas/phdlogin.php, username=ethics, password=ethics)

1) First set of results show the simulation results when agents believe in the forecasts.
2) Second set of results show the simulation results when agents do NOT believe in the forecasts.

After viewing the results, the users will answer a post-survey questionnaire with similar questions as the pre-survey. The total time for all of the tasks should be around 45 minutes. The objective of the post-survey is to help understand if there has been a change in the responses from the pre-survey. It is expected that the users are better able to understand fundamental market relationships between market components.

Electronic Pre-survey questionnaire: On a scale from 1-5, where 5 is very confident, and 1 is not very confident

1.How confident are you in the level of your knowledge of the impacts of load forecasts on electricity market prices? Check: 1,2,3,4,5,N/A

2.How confident are you in the level of your knowledge on identifying opportunities (such as particular hours NOT to avoid) in the electricity market using load forecasts? Check: 1,2,3,4,5,N/A

3.How confident are you in the level of your knowledge on identifying threats (such as particular hours to avoid) in the electricity market using load forecasts? Check: 1,2,3,4,5,N/A

Electronic Post-survey questionnaire: On a scale from 1-5, where 5 is very confident, and 1 is not very confident

1.After viewing the results, how confident are you in the level of your knowledge of the impacts of load forecast on the electricity market prices? Check: 1,2,3,4,5,N/A

2.After viewing the results, how confident are you in the level of your knowledge on identifying opportunities (such as particular hours NOT to avoid) in the electricity market using load forecasts? Check: 1,2,3,4,5, N/A

3.After viewing the results, how confident are you in the level of your knowledge on identifying potential threats (such as particular hours to avoid) in the electricity market using load forecasts? Check: 1,2,3,4,5,N/A

4) How confident are you that TRAMAS could be a useful decision support tool for learning electricity market fundamentals? Check: 1,2,3,4,5,N/A

5) Open ended question post-simulation: Provide any feedback you may have about TRAMAS.

3. Recruitment of Participants

3.1 Describe the "types" of participants (e.g. city planners, environmental specialists, minor age children, University students) to be involved in the research. Be very specific about your method(s) for recruiting them, and comment on who will do the recruiting. Describe how and where you will advertise your project. **Include a copy of your recruitment notice, advertisement, information sheet, as well as that used by a sponsor or supportive organization, if applicable.** If actively seeking participation by speaking to specific groups, include the text used for verbal presentations. If remuneration/compensation is offered, provide details, including amount and confirm the budget provisions to meet these obligations. Describe any provisions that have been made to accommodate the participants' language.

For 1) Seven to Ten (7-10) Experts in the electricity industry will be recruited by the applicant. They will be chosen for their knowledge of electricity trading. Emails will be sent to people known to the applicant as industry colleagues.

For 2) Participants of any level of knowledge in trading will be recruited by the applicant. While focus will be put on energy trading professionals, the success of the project is not dependent on energy traders. One place for recruitment are postings in LinkedIn groups: 1) Electric Utility Professionals, 2) Energy & Utilities Network, 3) Energy Trading, 4) Energy Trading Network, 5) Houston Energy Traders, 6) Hedge Fund Group (HFG).

For 1) the email will state the following:

Hello:

I am a PhD candidate in the Department of Electrical and Computer Engineering at The University of Calgary conducting research under the supervision of Professors Dr. Guenther Ruhe and Dr. Joerg Denzinger on the use of an Intelligent Decision Support System (IDSS) for Trading. Specifically, we want to evaluate the effectiveness of new technology that we have developed for traders: We call this technology TRAMAS. We have instantiated this new technology to help traders trade in the virtual day-ahead market in the PJM electricity market (http://www.pjm.com). This new technology is built on a multi-agent simulation (MAS) framework and is intended to be an intelligent decision support (IDSS) tool for traders. As an expert in the industry, your opinions will be important to this study. I would appreciate your participation in this study.

I plan to conduct this research online. Your involvement in this survey is entirely voluntary and there are no known or anticipated risks to participating in this study. If you agree to participate, the survey should not take more than about 45 minutes. The questions are specific to the financial trading of electricity in PJM and you will be asked to evaluate the following model constructs and provide your expert judgement on the validity of the model. Specifically, you will be asked to evaluate the causal model, model assumptions, model components, and model results.

For the model results you will answer the following questions:

a) How well has TRAMAS represented the PRICES for the actual virtual real-time PJM market?

b) How well has TRAMAS represented the PRICE TRENDS for the actual virtual real-time PJM market?

c) Looking at the results in Tables 1-9. How well has TRAMAS represented an ACTUAL virtual real-time PJM market?

d) From a scale from 1 to 5 where 1 is not very confident and 5 is very confident.

How confident would you be to use TRAMAS (in different simulations) to help you trade in the REAL PJM market?

All or some of your feedback will be included as part of the final PhD thesis. Furthermore, you will not be identified by name (or any other personal information) in any thesis, report or any future publication(s) resulting from this study. The data collected will be kept for a period of 1 year (from date of Ethics approval) in a secure password protected database only accessible by me (Sebastian Maurice). After 1 year or after successful defense of the PhD thesis (estimated to be complete by December 2012), all data will be permanently destroyed and will not be retrievable by anyone in whole or in part.

If after receiving this letter, you have any questions about this study, or would like additional information to assist you in reaching a decision about participation, please feel free to contact Sebastian Maurice at the email: sebastian.maurice@gmail.com or call me at 403-828-9431**. If you agree to participate, a URL and a username/password to the survey site will be sent to you.**

I would like to assure you that this study has been reviewed and received ethics clearance through the Conjoint Faculties Research Ethics Board at the University of Calgary, (Research Services, ERRB Building, Research Park) at (403) 210-9863. However, the final decision about participation is yours. If you have any concerns about the way you've been treated as a participant, please contact Russell Burrows, Senior Ethics Resource Officer, Research Services, University of Calgary at (403) 220-3782; e-mail rburrows@ucalgary.ca.

Thank you in advance for your interest in this project.

Yours sincerely,

Sebastian Maurice, PhD Candidate
University of Calgary, Schulich School of Engineering
Department of Electrical and Computer Engineering
Email: smaurice@ucalgary.ca

For 2) email below will be sent to people (non-experts) asking them to participate. There will be no remuneration/compensation being offered. The email and post will state the following:

Hello:

I am a PhD candidate in the Department of Electrical and Computer Engineering at The University of Calgary conducting research under the supervision of Professors Dr. Guenther Ruhe and Dr. Joerg Denzinger on the use of an Intelligent Decision Support System (IDSS) for Trading. Specifically, we want to evaluate the effectiveness of new technology that we have developed for traders: We call this technology TRAMAS. We have instantiated this new technology to help traders trade in the virtual day-ahead market in the PJM electricity market (http://www.pjm.com). This new technology is built on a multi-agent simulation (MAS) framework and is intended to be an intelligent decision support (IDSS) tool for traders. Your opinions will be important to this study. I would appreciate your participation in this study.
You will first answer a pre-survey questionnaire. Then you will be asked to review results from the simulation. You will view TWO result sets:

1) First set of results show the simulation results when agents believe in the load forecasts.
2) Second set of results show the simulation results when agents do NOT believe in the load forecasts.

After viewing the results, you will answer a post-survey questionnaire with similar questions as the pre-survey. The total time for all of the tasks should be around 45 minutes. The objective of the post-survey is to help understand if there has been a change in the responses from the pre-survey. It is expected that you are able to understand fundamental market relationships between market components after viewing the simulation results.

If after receiving this letter, you have any questions about this study, or would like additional information to assist you in reaching a decision about participation, please feel free to contact Sebastian Maurice at the email: sebastian.maurice@gmail.com or call me at 403-828-9431. **If you agree to participate, a URL and a username/password to the survey site will be sent to you.**
I would like to assure you that this study has been reviewed and received ethics clearance through the Conjoint Faculties Research Ethics Board at the University of Calgary, (Research Services, ERRB Building, Research Park) at (403) 210-9863. However, the final decision about participation is yours. If you have any concerns about the way you've been treated as a participant, please contact Russell Burrows, Senior Ethics Resource Officer, Research Services, University of Calgary at (403) 220-3782; e-mail rburrows@ucalgary.ca.
Thank you in advance for your interest in this project.

Yours sincerely,
Sebastian Maurice, PhD Candidate
University of Calgary, Schulich School of Engineering
Department of Electrical and Computer Engineering
Email: smaurice@ucalgary.ca

4. Informed Consent

4.1 Described the informed consent process. **Provide a copy of your consent form.** If there is no written consent form, please provide an explanation for this and details about your alternative procedures. If obtaining verbal consent, a script containing the same points normally covered by written consent is required. Are participants minors or, for other reasons, not able to provide fully informed consent? Explain and justify, and describe alternative procedures (e.g. parental consent).

Informed Consent Form

Purpose of the Study:
Purpose of the Study:
This is a study in online learning of electricity market fundamentals that is being conducted by Sebastian Maurice, PhD candidate at The University of Calgary in Calgary, Alberta, Canada. His PhD supervisors are: Dr Guenther Ruhe (ruhe@ucalgary.ca) and Dr. Joerg Denzinger (denzinge@cpsc.ucalgary.ca). **The University of Calgary Conjoint Faculties Research Ethics Board has approved this research study.** The purpose of this study is to examine the effectiveness of an intelligent decision support tool for trading in teaching users on electricity market fundamentals. Results of this study will be used to determine if users are more or less confident in participating in the real electricity market after they have used our intelligent decision support tool. At the end of the survey, a link will be automatically provided to you allowing you to view your survey results online.

What will be done for Experts:
Experts will be chosen by the applicant, and they will provide their expert judgements on the constructs of the model. Specifically, they will be asked to evaluate the causal model, model assumptions, model components, and model results.

All or some of your feedback will be included as part of the final PhD thesis . You will remain anonymous in the thesis, or report, or any type of publication resulting from this research.

What will be done for general participants:

You will complete a pre-survey questionnaire that will take you approximately 5 minutes to complete. The pre-survey questionnaire will ask you about your current understanding of the electricity market and specifically the day-ahead financial market see http://www.pjm.com and your confidence level in participating in this market (ignoring any financial requirements needed to participate).

Then you will be asked to review results from the simulation. The users will view TWO result sets:

1) First set of results show the simulation results when agents believe in the load forecasts.
2) Second set of results show the simulation results when agents do NOT believe in the load forecasts.

After viewing the results, you will answer a post-survey questionnaire with similar questions as the pre-survey. The total time for all of the tasks should be around 45 minutes. The objective of the post-survey is to help understand if there has been a change in the responses from the pre-survey. It is expected that you are able to understand fundamental market relationships between market components after viewing the simulation results, hence raising your confidence in using TRAMAS to help trade in the virtual real-time PJM market.

After you complete the questionnaire, we will analyse your responses in aggregate to determine if there is a change in user confidence levels and if people are more confident in their knowledge about electricity market fundamentals.

Benefits of this Study:
You will be contributing to knowledge about the effectiveness of using simulation technology to help teach users on electricity market fundamentals. This is important because electricity markets are very volatile, and the market is highly specialized, so training users on market fundamentals, before they actually participate in the real market, could help to reduce the financial risk for traders (market participants) in this market.

Risks or discomforts:
No risks or discomforts are anticipated from taking part in this study. If you feel uncomfortable with a question, you can skip that question or withdraw from the study altogether. If you decide to quit at any time before you have finished the questionnaire, and not pressed submit, your answers will NOT be recorded.

Confidentiality:
Your responses will be kept completely confidential. We will NOT know your IP address when you respond to the Internet survey. We will not ask for any personal information and your responses can not be linked to you directly in any way. Before submitting your responses you will have the option to not submit your responses, at which time absolutely no information will be recorded.

You will be assigned a participant number, and only the participant number will appear with your survey responses. Only the researchers will see your individual survey responses and the results of our content analysis. We will not store e-mail addresses of our participants. After we have finished data collection it will be kept in our databases for up to 1 year or up to the time of the successful thesis defense, after which time it will be completely destroyed. You can also view your responses on a website.

Decision to quit at any time:

Your participation is voluntary; you are free to withdraw your participation from this study at any time. If you do not want to continue, you can simply leave this website. If you do not click on the "submit" button at the end of the survey, your answers and participation will not be recorded. You also may choose to skip any questions that you do not wish to answer. If you click on the “submit” button at the end of the survey, your responses will be recorded and you will be anonymous to the system. This means we will not have any means to retrieve your information. Your participant number will not and cannot be used to retrieve information because no name or personal information is linked to this number; this number is only for general coding purposes.

How the findings will be used:

The results of the study will be used for scholarly purposes only as part of a PhD thesis. The results from the study will be presented in educational settings and at professional conferences, and the results might be published in a professional journal in the field of simulation technologies, decision support systems, software engineering, and multi-agent systems.

Contact information:

If you have concerns or questions about this study, please contact Sebastian Maurice at smaurice@ucalgary.ca (cell: 403-828-9431) or sebastian.maurice@gmail.com. . If you have any concerns about the way you’ve been treated as a participant, please contact Russell Burrows, Senior Ethics Resource Officer, Research Services, University of Calgary at (403) 220-3782; e-mail rburrows@ucalgary.ca.

By beginning the survey, you acknowledge that you have read this information and agree to participate in this research, with the knowledge that you are free to withdraw your participation at any time without penalty.

4.2 When and how will people be informed of the right to withdraw from the study? What procedures will be followed for people who wish to withdraw at any point during the study? What happens to the information contributed to this point? Please note that the CFREB does not require that researchers withdraw/destroy partial data in cases of participant withdrawal, provided that it is made clear on the informed consent form that data collected to the point of withdrawal will be retained/used.

All users will be sent emails asking to participate in the study. Even after they agree to participate they can choose to not submit their online responses and so not have their responses recorded.

It should be noted that all respondents are anonymous and there is no way to link responses to respondents after they have submitted their online responses.

4.3 Do you plan follow-up procedures with participants? [x] No [ ] Yes, if yes, what are they? Does your research design require formal debriefing? [x] No [ ] Yes, if yes, please provide details about the procedures you will use.

5. Privacy: Confidentiality and Anonymity:

5.1 Check all that apply: **Participant contributions will be: [x] public and cited; [x] anonymous; [x] confidential.** Explain the steps you propose to respect an individual's privacy. Describe these precautions in terms of access to raw data, as well as in terms of the write-up of the results. For example, will data be reported in aggregate? Will participants select a pseudonym? Will participants be asked to review their contribution before inclusion? (Please note that the CFREB does not require that participants be given the option of reviewing their data, provided they are aware that this opportunity will not be offered to them. Should you wish to provide participants with a chance to review material attributed to them, it is recommended that you set a specific time limit [e.g. within two weeks of receiving the material] by which participants must contact you with any suggested changes to material attributed to them, with a lack of response within that time indicating that the participant approves of the material as is, in order to avoid delays to your research. This timeline should be made clear in the consent protocol.) Who gets the data and in what form?

For the expert study, all data will be anonymous, no personal information will be collected. The responses from experts will be included as part of the final thesis. Respondents can review their online responses before submitting. They will have a choice to not submit their responses.

For participant or survey study, data will be analysed in aggregate form. All respondents will be anonymous and at no time will any personal information be collected and/or stored. Respondents can review their responses before submitting their responses and decide at that time to submit their response or not. After submitting, they cannot view their reponses because they are anonymous to the system and the system will not know who submitted the responses.

Only the applicant and his supervisor(s) get the data in electronic form only.

5.2 Provide specific details about the security procedures for the data as well as plans for the ultimate disposal of records/data. Who will have access to confidential data now or in the future? Specify the length of time the data will be retained and the plans for disposal of records/data. (Note: The CFREB does not have specific data retention or destruction requirements. Researchers are free to retain data for long periods of time, or archive data indefinitely, provided this is made clear to participants in the informed consent protocol, and continued/future use of the data is consistent with what is described by the researcher[s] within this application.) • All data will be stored electronically in a secure database only accessible to the applicant and his PhD supervisor(s). The database is secured by a strong password that is known only to the applicant. • The data will kept in its electronic form for a period of 1 year or up to the time of the successful thesis defense, after which time it will be permanently destroyed from the database it is stored in. • The procedure for data capture, storage and destruction will be made clear and explicit to all respondents. • All respondents will receive an anonymous login. At no time will the name or any other personal information of the respondents be stored in the database that can directly link them to their responses. Except to identify them as expert, or non-expert. • Absolutely NO personal information will be collected as part of this research.			
6. Estimation of Risks: Will this study involve the following? Please check Y When responding, see also Section 3– Information to Help Applicants	None	Minimal Risk	More than Minimal risk
6.1 Psychological or emotional manipulations – might a participant feel demeaned, embarrassed, worried or upset? Could subjects feel fatigued or stressed?	x		
6.2 Are there questions that may be upsetting to the respondent?	x		
6.3 Does your study have the potential for identifying distressed individuals?	x		
6.4 Is there any physical risk or physiological manipulation?	x		
6.5 Is any deception involved? Withholding of information from, or misinforming, participants?	x		
6.6 Is there any social risk - possible loss of status, privacy and/or reputation?	x		
6.7 Do you see any chance that subjects might be harmed in any way?	x		
6.8 Is there any potential for the perception of coercion? That is, might prospective participants feel pressured to participate in the research (due to, for instance, actual or perceived power relationships between those involved in recruiting and those being recruited, e.g. manager/employee or teacher/student)?	x		

6.9 Are the risks similar to those encountered by the subjects in everyday life?	[x]Yes [ ] No if "no" , elaborate

- If you answered, "more than minimal risk" to any of the above, describe the manipulations and/or potential risks as well as the safeguards or procedures you have in place. Please provide justification for any risks involved and explain why alternative approaches involving less risk cannot be used. Use additional pages, as required.
- If your study has the potential to upset or distress individuals, arrangements must be made to mitigate such effects. Describe the arrangements you have made. Have participants been informed of any costs to be incurred by them for services? **See "Provision for Rescue – Guidelines for Applicants"**
- If your study has the potential to identify upset or distressed individuals, you must describe the arrangements you have made (if any) to assist these individuals. If you do not make any arrangements, please explain why. Have participants been informed of any costs to be incurred by them for services?
- If, prior to the start of the research session, participants will not be fully informed of everything that will be required of them or deliberately misinformed about some aspect of the study, explain why. Please describe the procedures in detail and justify why deception is necessary to conduct the research.
- If the potential for any perception of coercion exists, please explain what measures have been put in place to minimize the possibility that individuals will feel pressured to participate.

Appendix B **Ethics Approval**

This study has received formal ethics approval from the University of Calgary Ethics Review Board.

Appendix C Table Schemas

The following table schemas are used to store simulation data. The schemas below are used in all analysis in case study #2.

Table 6-1: Simulation Variables (Physical table name: TRAMAS_BID_DECISIONS)

Variable	Data Type	Description
SESSID	TEXT	Web session ID
SIMID	NUMBER	Simulation ID (PMO ID)
ROUND	NUMBER	Simulation round number
HOUR	NUMBER	Trading hour: 1-24
AGENTID	NUMBER	Agent id
AGENTTYPE	TEXT	Agent type: expagg, expnonagg, inexpagg, inexpnonagg
DECISIONVAR	TEXT	alpha (α) or beta (β)
VALUE	NUMBER	DECISIONVAR value
COEFFNAME	TEXT	C1 or C2
COEFFVALUE	NUMBER	COEFFNAME value
PRICE	NUMBER	Bid price
QUANTITY	NUMBER	Bid quantity
PROBREWARD	NUMBER	Probability of reward
UPPER	NUMBER	In Bid Submission Process: upper constraint
CENTER	NUMBER	In Bid Submission Process: center constraint
LOWER	NUMBER	In Bid Submission Process: lower constraint
MINREWARD	NUMBER	Minimum reward threshold
DATE	TEXT	Date
BUYERWINS	NUMBER	1 if buyer wins the trade, 0 otherwise
SELLERWINS	NUMBER	1 if seller wins the trade, 0 otherwise
FORECASTDATE	TEXT	Date of forecast
AGENTCLEARED	NUMBER	1 if agent cleared the trade, 0 otherwise
AGENTWON	NUMBER	1 if agent won the trade, 0 otherwise

POSITION	TEXT	**s** for sell, **b** for buy
CLEAREDPRICE	NUMBER	Cleared market price
CLEAREDQUANTITY	NUMBER	Cleared market quantity
BASEPRICE	NUMBER	Base price
ACTUALFORECAST	NUMBER	Actual forecast
MODIFIEDFORECAST	NUMBER	User modified forecast
SETTLEDPRICE	NUMBER	This is the real average historical price for this hour
MARKET	TEXT	LoadForecast or weatherForecast
MPARAM1	TEXT	Additional simulation parameter
MPARAM2	TEXT	Additional simulation parameter
MPARAM3	TEXT	Additional simulation parameter

The following table stores the actual market data for the validation analysis.

Table 6-2: Historical Raw Data (Physical Table name: PhDData)

Variable	Data Type	Description
EFFECTIVE_DATE	DATE	Date period of the data
EFFECTIVE_HOUR	NUMBER	Hour period of the data
RTLMP	NUMBER	Real-time prices
ATEMP	NUMBER	Weather forecast
ADALMP	NUMBER	Day-ahead prices
ALOAD	NUMBER	Load forecast
AGENTID	NUMBER	Agent id
SIMID	NUMBER	Simulation id
ROUND	NUMBER	Simulation round
AGENTTYPE	TEXT	Type of agent

The next table shows the ACCUMULATE_KNOWLEDGE table used in the agents' learning process.

Table 6-3: Accumulate Knowledge Table

Variable	Data Type	Description
SIMID	NUMBER	Simulation id
AGENTID	NUMBER	Agent id
AGENTTYPE	TEXT	Type of agent
EFFECTIVE_DATE	DATE	Date period of the data
EFFECTIVE_HOUR	NUMBER	Hour period of the data
RTLMP	NUMBER	Real-time prices
ADALMP	NUMBER	Day-ahead prices
TRADER	TEXT	Indicated the type of trader: buyer or seller
BETA	NUMBER	Value of the Beta parameter
MODIFIED	NUMBER	Modified forecast value
FORECAST	NUMBER	Original forecast value
ALPHA	NUMBER	Value of the Alpha parameter
BUYERWINS	NUMBER	1 if buyer wins, 0 otherwise
SELLERWINS	NUMBER	1 if seller wins, 0 otherwise
DATE	DATE	Current date

Appendix D Best Trades

This appendix shows the best trades[33] for each PMO. These trades are shown in Table 6-4 to Table 6-8.

Table 6-4: Best Trades (1/5)

125112				450745				186270			
Hour	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**
1	b	26.45	0.6	1	b	24.18	0.62	1	b	25.93	0.6
2	b	25.13	0.6	2	b	22.89	0.61	2	b	24.78	0.6
3	b	22.3	0.6	3	b	21.78	0.61	3	b	22.11	0.6
4	b	21.26	0.59	4	b	21.09	0.6	4	b	21.36	0.59
5	b	20.98	0.6	5	b	21.95	0.6	5	b	20.72	0.6
6	b	23.55	0.6	6	b	24.45	0.59	6	b	22.83	0.6
7	b	28.35	0.6	7	b	32.89	0.6	7	b	27.83	0.59
8	b	28.93	0.6	8	b	33.9	0.66	8	b	28.62	0.6
9	b	33.16	0.6	9	b	35.08	0.61	9	b	32.77	0.59
10	b	36.74	0.6	10	b	37.15	0.62	10	b	36.83	0.6
11	b	42.09	0.6	11	b	38.92	0.64	11	b	42.79	0.59
12	b	44.81	0.59	12	b	39.82	0.6	12	b	44.41	0.61
13	b	44.26	0.6	13	b	38.03	0.6	13	b	45.11	0.59
14	b	48.45	0.6	14	b	38.45	0.6	14	b	48.86	0.59
15	b	47.74	0.6	15	b	40.72	0.6	15	b	48.08	0.6
16	b	49.9	0.6	16	b	39.08	0.6	16	b	50.61	0.6
17	b	53.52	0.59	17	b	42.98	0.61	17	b	52.22	0.6
18	b	50.93	0.6	18	b	51.93	0.59	18	b	50.29	0.6
19	b	43.77	0.6	19	b	43.27	0.59	19	b	43.46	0.6
20	b	43.19	0.6	20	b	40.84	0.6	20	b	43.61	0.59
21	b	44.53	0.6	21	b	44	0.6	21	b	44.3	0.59
22	b	39.61	0.6	22	b	37.18	0.6	22	b	40.06	0.59
23	b	31.55	0.6	23	b	30.13	0.59	23	b	30.71	0.61
24	b	28.04	0.6	24	b	26.86	0.6	24	b	27.9	0.6
1	s	24.22	0.65	1	s	22.86	0.65	1	s	23.75	0.65
2	s	23.46	0.65	2	s	21.65	0.65	2	s	23.05	0.65
3	s	20.77	0.65	3	s	20.84	0.65	3	s	20.99	0.65
4	s	19.9	0.64	4	s	20.17	0.65	4	s	19.86	0.65
5	s	19.5	0.65	5	s	20.62	0.65	5	s	19.04	0.65
6	s	21.61	0.65	6	s	22.33	0.65	6	s	21.35	0.65

[33] http://people.ucalgary.ca/~smaurice/PhD%20Research-SQL%20Queries.pdf, see Table 6.

7	s	25.81	0.65	7	s	30.3	0.65	7	s	25.02	0.65
8	s	26.41	0.65	8	s	31.27	0.65	8	s	25.41	0.65
9	S	30.29	0.65	9	s	30.24	0.65	9	s	30.05	0.65
10	S	34.1	0.65	10	s	33.93	0.65	10	s	33.87	0.65
11	S	38.65	0.65	11	s	35.79	0.65	11	s	38.88	0.65
12	S	41.44	0.64	12	s	37.22	0.65	12	s	40.51	0.65
13	S	41.11	0.65	13	s	35.76	0.65	13	s	41.55	0.65
14	S	45.2	0.65	14	s	36.66	0.65	14	s	43.8	0.65
15	S	42.88	0.65	15	s	37.47	0.65	15	s	41.67	0.65
16	S	45.96	0.65	16	s	36.57	0.65	16	s	44.02	0.65
17	S	48.9	0.65	17	s	40.44	0.65	17	s	46.72	0.65
18	S	47.25	0.65	18	s	48.01	0.65	18	s	47.32	0.65
19	S	40.32	0.65	19	s	40.54	0.65	19	s	39.95	0.65
20	S	40.32	0.65	20	s	38.39	0.65	20	s	40.5	0.65
21	S	41.54	0.64	21	s	39.05	0.65	21	s	41.08	0.65
22	S	36.68	0.65	22	s	34.44	0.65	22	s	37	0.65
23	S	28.18	0.65	23	s	27.92	0.65	23	s	28.68	0.65
24	S	25.91	0.65	24	s	24.87	0.65	24	s	25.71	0.65

Table 6-5: Best Trades (2/5)

220354				252884				281206			
Hour	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**
1	b	75.23	0.63	1	b	29.7	0.58	1	b	26.59	0.6
2	b	34.47	0.62	2	b	27.67	0.58	2	b	24.73	0.6
3	b	23.51	0.63	3	b	25.48	0.58	3	b	23.32	0.6
4	b	78.2	0.61	4	b	24.22	0.58	4	b	22.67	0.6
6	b	15.77	0.63	5	b	23.74	0.59	5	b	22.23	0.6
7	b	15.22	0.61	6	b	24.26	0.59	6	b	23.93	0.61
8	b	132.15	0.63	7	b	30.03	0.59	7	b	29.22	0.6
9	b	69.4	0.62	8	b	29.98	0.59	8	b	29.4	0.61
10	b	75.45	0.61	9	b	31.48	0.59	9	b	29.49	0.6
11	b	82.73	0.62	10	b	36.41	0.6	10	b	33.35	0.59
12	b	51.99	0.63	11	b	41.28	0.59	11	b	35.4	0.6
13	b	113.92	0.62	12	b	44.5	0.58	12	b	36.13	0.6
14	b	223.17	0.62	13	b	45.53	0.58	13	b	34.65	0.61
15	b	247.46	0.63	14	b	49.4	0.58	14	b	34.96	0.62
16	b	103.38	0.62	15	b	49.26	0.58	15	b	37.32	0.61
17	b	91.15	0.61	16	b	51.8	0.58	16	b	35.31	0.62
18	b	150.9	0.61	17	b	53.96	0.59	17	b	38.46	0.6
19	b	77.52	0.62	18	b	57.4	0.58	18	b	46.33	0.6
20	b	31.95	0.62	19	b	49.31	0.58	19	b	39.6	0.62

21	b	46.8	0.62	20	b	46.22	0.59	20	b	37.18	0.6
22	b	46.36	0.62	21	b	45.02	0.58	21	b	38.25	0.6
23	b	27.72	0.63	22	b	40.5	0.58	22	b	34.59	0.6
24	b	48.63	0.62	23	b	32.62	0.58	23	b	28.61	0.59
9	s	67.04	0.64	24	b	29.69	0.59	24	b	25.77	0.6
10	s	81	0.63	1	s	28.41	0.66	3	s	21.32	0.65
11	s	374.05	0.64	2	s	26.88	0.66	17	s	34.69	0.64
13	s	58.46	0.64	3	s	24.53	0.66	18	s	41.7	0.64
14	s	443.88	0.64	4	s	23.23	0.66				
16	s	51.41	0.64	5	s	22.99	0.66				
17	s	63.02	0.63	6	s	23.62	0.66				
19	s	177.67	0.63	7	s	28.75	0.66				
20	s	155.98	0.64	8	s	29.24	0.66				
22	s	39.9	0.64	9	s	30.16	0.66				
23	s	48.99	0.64	10	s	35.3	0.66				
				11	s	40.08	0.66				
				12	s	42.93	0.66				
				13	s	44.3	0.66				
				14	s	47.48	0.66				
				15	s	46.77	0.66				
				16	s	49.74	0.66				
				17	s	51.81	0.66				
				18	s	55.65	0.66				
				19	s	47.12	0.66				
				20	s	44.51	0.66				
				21	s	43.71	0.66				
				22	s	39.14	0.66				
				23	s	31.69	0.66				
				24	s	29.15	0.66				

Table 6-6: Best Trades (3/5)

328797				404557				527938			
Hour	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**	**Hour**	**Position**	**Price**	**Prob. of Reward**
1	b	24.96	0.63	1	b	75.22	0.63	1	b	26.45	0.6
2	b	23.57	0.63	2	b	34.47	0.62	2	b	25.18	0.6
3	b	19.48	0.62	3	b	23.51	0.63	3	b	22.25	0.6
4	b	18.06	0.62	4	b	78.2	0.61	4	b	21.31	0.6
5	b	15.86	0.62	6	b	15.77	0.63	5	b	21.37	0.6
6	b	18.52	0.62	7	b	15.22	0.61	6	b	23.36	0.6
7	b	17.72	0.63	8	b	132.45	0.64	7	b	28.65	0.6
8	b	19.07	0.63	9	b	56.96	0.62	8	b	28.96	0.61

9	b	32.17	0.62	10	b	62.6	0.62	9	b	33.15	0.61
10	b	36.47	0.62	11	b	71.19	0.62	10	b	36.84	0.61
11	b	47.21	0.63	12	b	51.8	0.63	11	b	42.74	0.6
12	b	52.83	0.61	13	b	94.48	0.62	12	b	43.15	0.62
13	b	57.72	0.62	14	b	170.78	0.62	13	b	43.42	0.61
14	b	68.28	0.61	15	b	186.19	0.62	14	b	47.43	0.61
15	b	66.94	0.62	16	b	93.87	0.62	15	b	47.89	0.6
16	b	74.46	0.61	17	b	88.84	0.61	16	b	48.77	0.6
17	b	73.88	0.63	18	b	126.86	0.61	17	b	53.78	0.6
18	b	54.06	0.63	19	b	66.63	0.61	18	b	51.29	0.6
19	b	43.35	0.62	20	b	35.39	0.62	19	b	44.93	0.6
20	b	44.22	0.63	21	b	46.71	0.62	20	b	43.93	0.6
21	b	46.4	0.62	22	b	46.37	0.62	21	b	44.46	0.6
22	b	45.36	0.62	23	b	29.14	0.63	22	b	39.99	0.6
23	b	31.39	0.62	24	b	48.63	0.62	23	b	31.01	0.6
24	b	27.98	0.63	9	s	80.15	0.64	24	b	28.07	0.6
1	s	22.11	0.63	10	s	92.2	0.63	1	s	24.73	0.65
2	s	21.91	0.63	11	s	276.99	0.64	2	s	23.93	0.65
3	s	17.77	0.62	12	s	274.2	0.64	3	s	21	0.65
4	s	16.56	0.62	13	s	225.03	0.64	4	s	19.83	0.65
5	s	14.51	0.63	14	s	281.42	0.64	5	s	19.39	0.65
6	s	17.22	0.63	16	s	51.41	0.64	6	s	21.93	0.65
7	s	16.49	0.62	17	s	258.05	0.63	7	s	26.54	0.64
8	s	17.19	0.63	18	s	37.73	0.64	8	s	27	0.65
9	s	28.54	0.63	19	s	170.97	0.64	9	s	30.99	0.65
10	s	33.59	0.63	20	s	105.46	0.64	10	s	35.31	0.65
11	s	43.14	0.62	21	s	45.23	0.64	11	s	40.36	0.65
12	s	48.15	0.62	22	s	22.42	0.63	12	s	41.12	0.65
13	s	52.91	0.63	23	s	52.61	0.64	13	s	40.74	0.65
14	s	63.03	0.62					15	s	45.32	0.65
15	s	58.9	0.63					17	s	51.33	0.65
16	s	67.12	0.62					18	s	48.43	0.65
17	s	67.42	0.63					19	s	41.51	0.65
18	s	49.73	0.63					20	s	41.2	0.65
19	s	39.38	0.62					21	s	42.17	0.65
20	s	40.98	0.63					22	s	37.6	0.65
21	s	42.47	0.63					23	s	29.43	0.65
22	s	40.94	0.62					24	s	26.46	0.65
23	s	28.7	0.63								
24	s	26.18	0.63								

Table 6-7: Best Trades (4/5)

533578				69839				12737			
Hour	Position	Price	Prob. of Reward	Hour	Position	Price	Prob. of Reward	Hour	Position	Price	Prob. of Reward
1	b	30.33	0.58	1	b	25.71	0.6	1	b	25.8	0.59
2	b	28.24	0.58	2	b	24.61	0.6	2	b	24.66	0.59
3	b	25.69	0.58	3	b	22.24	0.6	3	b	22.79	0.6
4	b	24.29	0.58	4	b	21.19	0.59	4	b	21.53	0.6
5	b	23.92	0.58	5	b	20.79	0.6	5	b	21.11	0.59
6	b	24.62	0.58	6	b	22.87	0.6	6	b	23.09	0.6
7	b	29.98	0.58	7	b	27.56	0.59	7	b	27.5	0.6
8	b	30.26	0.59	8	b	28.43	0.6	8	b	28.11	0.6
9	b	32.12	0.59	9	b	32.65	0.6	9	b	33.17	0.6
10	b	37.14	0.58	10	b	36.9	0.6	10	b	36.82	0.6
11	b	42.51	0.58	11	b	41.44	0.6	11	b	42	0.6
12	b	45.43	0.58	12	b	44.11	0.59	12	b	44.62	0.6
13	b	45.56	0.59	13	b	44.09	0.6	13	b	44.76	0.59
14	b	49.84	0.59	14	b	48.46	0.6	14	b	49.58	0.59
15	b	50.05	0.59	15	b	46.35	0.6	15	b	47.46	0.59
16	b	52.48	0.58	16	b	49.15	0.6	16	b	50.4	0.6
17	b	55.26	0.58	17	b	51.81	0.6	17	b	52.88	0.6
18	b	58.1	0.58	18	b	50.78	0.6	18	b	50.55	0.59
19	b	49.5	0.58	19	b	42.95	0.6	19	b	43.24	0.59
20	b	46.81	0.58	20	b	42.91	0.6	20	b	42.99	0.59
21	b	46.12	0.59	21	b	43.42	0.6	21	b	44.47	0.59
22	b	40.63	0.59	22	b	39.36	0.6	22	b	40.03	0.6
23	b	32.9	0.59	23	b	30.65	0.6	23	b	30.78	0.6
24	b	29.85	0.59	24	b	28.03	0.6	24	b	28.14	0.59
1	s	28.4	0.66	1	s	23.74	0.65	1	s	24.09	0.65
2	s	26.65	0.66	2	s	23.15	0.65	2	s	23.28	0.65
3	s	24.16	0.66	3	s	20.98	0.64	3	s	20.76	0.65
4	s	23.03	0.66	4	s	20.02	0.65	4	s	19.85	0.65
5	s	22.56	0.66	5	s	19.77	0.65	5	s	19.39	0.65
6	s	23.17	0.66	6	s	21.75	0.65	6	s	21.45	0.64
7	s	28.46	0.66	7	s	26.17	0.64	7	s	25.71	0.65
8	s	28.74	0.66	8	s	26.44	0.65	8	s	25.84	0.65
9	s	29.91	0.66	9	s	30.47	0.65	9	s	30.18	0.65
10	s	34.72	0.66	10	s	34.1	0.65	10	s	33.59	0.65
11	s	39.49	0.66	11	s	38.54	0.65	11	s	38.59	0.65

12	s	42.32	0.66	12	s	40.92	0.65	12	s	41.5	0.64
13	s	43.42	0.66	13	s	41.19	0.65	13	s	41.13	0.65
14	s	46.75	0.67	14	s	45.21	0.65	14	s	45.43	0.65
15	s	46	0.66	15	s	42.94	0.65	15	s	43.98	0.65
16	s	48.96	0.66	16	s	45.98	0.65	16	s	46.48	0.65
17	s	51.26	0.66	17	s	48.32	0.65	17	s	49.36	0.65
18	s	55.23	0.66	18	s	47.04	0.65	18	s	47.48	0.65
19	s	46.23	0.66	19	s	40.17	0.65	19	s	40.66	0.65
20	s	43.61	0.66	20	s	40.06	0.64	20	s	40.45	0.65
21	s	42.91	0.66	21	s	40.58	0.64	21	s	41.17	0.65
22	s	38.45	0.66	22	s	36.8	0.65	22	s	36.75	0.65
23	s	31.21	0.66	23	s	28.58	0.65	23	s	28.6	0.65
24	s	28.57	0.66	24	s	25.93	0.64	24	s	25.89	0.65

Table 6-8: Best Trades (5/5)

954178			
Hour	**Position**	**Price**	**Prob. of Reward**
1	b	43.13	0.63
2	b	23.39	0.62
3	b	31.4	0.62
4	b	23.84	0.61
5	b	41.44	0.62
6	b	31.38	0.63
7	b	64.34	0.61
8	b	64.26	0.64
9	b	55.89	0.62
10	b	18.25	0.62
11	b	64.66	0.63
12	b	52.37	0.63
13	b	56.13	0.62
14	b	66.66	0.62
15	b	65.09	0.62
16	b	75.95	0.62
17	b	81.9	0.61
18	b	56.03	0.61
19	b	45.12	0.61
20	b	33.79	0.61
21	b	88.09	0.62
22	b	65.39	0.62
23	b	50.08	0.63

24	b	39.18	0.63
1	s	24.36	0.63
2	s	16.37	0.63
3	s	17.26	0.63
4	s	16.36	0.62
5	s	25.16	0.63
6	s	20.46	0.64
7	s	11.84	0.63
8	s	72.28	0.64
9	s	36.97	0.63
10	s	57.5	0.63
11	s	52.68	0.63
12	s	67.21	0.64
13	s	33.97	0.63
14	s	107.38	0.63
15	s	69.35	0.63
16	s	63.6	0.63
17	s	105.65	0.63
18	s	115.99	0.63
19	s	57.85	0.63
20	s	40.14	0.63
21	s	68.56	0.63
22	s	38.98	0.63
23	s	29.52	0.63
24	s	41.36	0.63

Appendix E **Agent Strategies**

Table 6-9 shows the strategy lables used to identify the strategies in Table 6-10. This table shows the average profits from the last round of trades over all traded hours.

Table 6-9: Strategy Labels

Strategy	Values
A	$(\alpha_t, \beta_t) = \{\alpha_t^c + \frac{1}{2}\lambda, \beta_t^c + \frac{1}{2}\lambda\}$
B	$(\alpha_t, \beta_t) = \{\alpha_t^c, \beta_t^c + \frac{1}{2}\lambda\}$
C	$(\alpha_t, \beta_t) = \{\alpha_t^c + \frac{1}{2}\lambda, \beta_t^c\}$
D	$(\alpha_t, \beta_t) = \{\alpha_t^c, \beta_t^c - \frac{1}{2}\lambda\}$
E	$(\alpha_t, \beta_t) = \{\alpha_t^c - \frac{1}{2}\lambda, \beta_t^c\}$
F	$(\alpha_t, \beta_t) = \{\alpha_t^c, \beta_t^c\}$
G	$(\alpha_t, \beta_t) = \{\alpha_t^c - \frac{1}{2}\lambda, \beta_t^c - \frac{1}{2}\lambda\}$
H	$(\alpha_t, \beta_t) = \{\alpha_t^c - \frac{1}{2}\lambda, \beta_t^c + \frac{1}{2}\lambda\}$
I	$(\alpha_t, \beta_t) = \{\alpha_t^c + \frac{1}{2}\lambda, \beta_t^c - \frac{1}{2}\lambda\}$

Table 6-10: Agent Strategies

simid	agenttype	C1	C2	A	B	C	D	E	F	G	H	I	Sum Profit
220354	expagg	-$0.36	$0.03	$0	-$15	$0	-$25	-$20	$0	-$3,539	-$1,951	$0	**-$5,549**
220354	expnonagg	-$0.49	$0.03	$0	-$8	$0	-$17	-$8	$0	-$1,334	-$821	$0	**-$2,189**
220354	inexpagg	$0.22	$0.03	$571	$3	$6	$4	$0	$0	$0	$0	$889	**$1,473**
220354	inexpnonagg	$0.11	$0.02	$184	$241	$2	$460	$0	$2	$0	$0	$276	**$1,165**
252884	expagg	-$0.26	$0.02	$0	-$53	$0	-$78	-$3	-$1	-$654	-$328	$0	**-$1,117**
252884	expnonagg	$0.01	$0.02	-$19	-$46	$0	-$68	-$2	$0	-$483	-$241	-$41	**-$901**
252884	inexpagg	$0.25	$0.03	$404	$0	$4	$0	$0	$0	$0	$0	$633	**$1,041**
252884	inexpnonagg	$0.24	$0.03	$332	$0	$3	$0	$0	$0	$2	$2	$534	**$874**
281206	expagg	$0.49	$0.03	-$109	-$8	-$1	-$8	$0	$0	$0	$0	-$140	**-$266**
281206	expnonagg	$0.53	$0.03	$160	$17	$2	$26	$0	$0	$0	$0	$257	**$462**
281206	inexpagg	-$0.34	$0.03	$0	$3	$0	$2	$1	$0	$165	$128	$0	**$299**
281206	inexpnonagg	-$0.35	$0.03	$0	$3	$0	$3	$3	$0	$418	$264	$0	**$691**
404557	expagg	-$0.48	$0.03	$0	-$10	$0	-$19	-$20	$0	-$3,709	-$2,028	$0	**-$5,786**
404557	expnonagg	-$0.37	$0.03	$0	-$2	$0	-$1	-$10	$0	-$1,642	-$1,030	$0	**-$2,684**

404557	inexpagg	$0.22	$0.03	$593	$7	$6	$7	$0	$0	$0	$0	$916	**$1,530**
404557	inexpnonagg	$0.12	$0.02	$347	$257	$3	$480	$0	$3	$0	$0	$402	**$1,491**
450745	expagg	$0.09	$0.03	-$5	-$7	$0	$13	$0	$0	-$4	-$3	-$1	**-$6**
450745	expnonagg	-$0.05	$0.04	$0	-$157	$0	-$250	$0	-$2	$8	$10	$0	**-$390**
450745	inexpagg	$0.09	$0.02	-$8	$12	$0	-$2	$0	$0	$0	$0	-$46	**-$45**
450745	inexpnonagg	$0.04	$0.03	-$20	$149	$0	$254	$0	$1	$0	$0	-$48	**$336**
533578	expagg	-$0.26	$0.02	$0	-$59	$0	-$89	-$3	-$1	-$584	-$290	$0	**-$1,026**
533578	expnonagg	-$0.06	$0.02	-$17	-$48	$0	-$74	-$3	$0	-$514	-$277	-$37	**-$971**
533578	inexpagg	$0.20	$0.03	$430	$0	$4	$0	$0	$0	$26	$23	$707	**$1,191**
533578	inexpnonagg	$0.22	$0.03	$350	-$13	$3	-$21	$0	$0	-$3	$0	$574	**$890**
954178	expagg	-$0.50	$0.04	$0	-$25	$0	-$57	-$12	$0	-$1,877	-$1,275	$0	**-$3,246**
954178	expnonagg	-$0.50	$0.03	$0	$9	$0	$17	-$4	$0	-$628	-$393	$0	**-$999**
954178	inexpagg	$0.22	$0.03	$263	$0	$3	$0	$0	$0	$0	$0	$458	**$724**
954178	inexpnonagg	$0.12	$0.02	-$146	-$40	-$1	-$163	$0	-$1	$0	$0	-$164	**-$515**
125112	expagg	-0.17	0.03	0.78	-16.1	-0	-28.4	-1.7	-0	-152.3	-180.7	-1.46	**-$380**
125112	expnonagg	-0.13	0.03	8.2	-16.8	0	-21	-1.8	-0	-171.1	-169.8	-2.71	**-$375**
125112	inexpagg	0.157	0.03	175	12.9	3	10.8	-0	0	-0.549	-3.211	285	**$482**
125112	inexpnonagg	0.165	0.03	285	20.1	4	13.8	-0	0	-0.965	-1.443	443	**$763**
186270	expagg	-0.28	0.05	2.04	-5.08	0	-9.24	-0.3	-0	-60.12	1.465	4.18	**-$67**
186270	expnonagg	-0.32	0.04	0.17	0.25	0	-2.07	-0.8	-0	-68.06	-68.88	0.39	**-$139**
186270	inexpagg	0.196	0.04	110	-0.37	1	1.4	0	0	0	0	162	**$275**
186270	inexpnonagg	0.131	0.02	344	54.9	4	47.5	-0	1	-0.456	-1.017	446	**$896**
328797	expagg	-0.45	0.03	0	-9.63	0	-18.2	-7.5	-0	-834.1	-591.7	0	**-$1,461**
328797	expnonagg	-0.66	0.04	0	-37.9	0	-61.7	-11	-1	-1037	-1039	0	**-$2,187**
328797	inexpagg	0.269	0.04	691	-0.23	9	-0.55	0	-0	0	0	1031	**$1,730**
328797	inexpnonagg	0.255	0.04	619	0	8	0	0	0	0	0	877	**$1,503**
527938	expagg	0.009	0.03	17.6	-79.1	0	-106	-0.3	-1	5.852	-36.32	20.7	**-$179**
527938	expnonagg	-0.16	0.03	6.63	-58.8	0	-40.1	-7.1	-1	-601.4	-674.5	0.86	**-$1,375**
527938	inexpagg	0.183	0.04	161	7.82	2	2.67	0	0	0	0	251	**$425**
527938	inexpnonagg	0.061	0.05	72.3	26.5	1	14.4	-0.1	0	-11.24	-8.687	141	**$235**
12737	expagg	0.301	0.02	213	0.72	4	0.37	-0	0	-0.569	-0.724	158	**$375**
12737	expnonagg	0.317	0.02	473	34	8	23.6	-0	1	-1.402	-2.214	329	**$865**
12737	inexpagg	-0.19	0.02	-1.73	-16.2	-0	-10.9	-4.7	-0	-190.4	-259.8	-1.08	**-$485**
12737	inexpnonagg	-0.21	0.02	-15.9	-48.4	-0	-36.3	-6.9	-1	-277.3	-393.2	-18.6	**-$798**
69839	expagg	0.28	0.01	275	0.02	5	-0.22	-0	-0	-0.055	-0.055	213	**$492**
69839	expnonagg	0.298	0.02	451	8.23	9	4.93	-0	0	-1.515	-1.912	385	**$855**
69839	inexpagg	-0.19	0.01	0.44	-0.81	0	0.4	-1.2	-0	-41.22	-65.86	0.42	**-$108**
69839	inexpnonagg	-0.26	0.01	0	-12	0	-8.36	-1.8	-0	-69.42	-104.2	0	**-$196**
Avg Profits				$138	$1	$2	$3	-$2	$0	-$344	-$227	$190	

Appendix F **Updating Strategy Variables**

Table 6-11 shows how the strategy variables will be updated based on the coefficients' values.

Table 6-11: Updating Strategy Variables

$\begin{pmatrix} \alpha_{it+1}^{a,U} \\ \beta_{it+1}^{a,U} \\ \alpha_{it+1}^{a,L} \\ \beta_{it+1}^{a,L} \end{pmatrix}$	$\hat{c}_{2i}^{a} > 0$	$\hat{c}_{2i}^{a} = 0$	$\hat{c}_{2i}^{a} < 0$
$\hat{c}_{1i}^{a} > 0$	$\begin{pmatrix} \alpha_{it}^{a,U} \\ \beta_{it}^{a,U} \\ \alpha_{it}^{a,c} \\ \beta_{it}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,U} \\ \beta_{it}^{a,c} + \frac{1}{2}\lambda_i^a \\ \alpha_{it}^{a,c} \\ \beta_{it}^{a,c} - \frac{1}{2}\lambda_i^a \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,U} \\ \beta_{it}^{a,c} \\ \alpha_{it}^{a,c} \\ \beta_{it}^{a,L} \end{pmatrix}$
$\hat{c}_{1i}^{a} = 0$	$\begin{pmatrix} \alpha_{it}^{a,c} + \frac{1}{2}\lambda_i^a \\ \beta_{it}^{a,U} \\ \alpha_{it}^{a,c} - \frac{1}{2}\lambda_i^a \\ \beta_{it}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,U} \\ \beta_{it}^{a,U} \\ \alpha_{it}^{a,L} \\ \beta_{it}^{a,L} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,c} + \frac{1}{2}\lambda_i^a \\ \beta_{it}^{a,c} \\ \alpha_{it}^{a,c} - \frac{1}{2}\lambda_i^a \\ \beta_{it}^{a,L} \end{pmatrix}$
$\hat{c}_{1i}^{a} < 0$	$\begin{pmatrix} \alpha_{it}^{a,c} \\ \beta_{it}^{a,U} \\ \alpha_{it}^{a,L} \\ \beta_{it}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,c} \\ \beta_{it}^{a,c} + \frac{1}{2}\lambda_i^a \\ \alpha_{it}^{a,L} \\ \beta_{it}^{a,c} - \frac{1}{2}\lambda_i^a \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{a,c} \\ \beta_{it}^{a,c} \\ \alpha_{it}^{a,L} \\ \beta_{it}^{a,L} \end{pmatrix}$
$\begin{pmatrix} \alpha_{it+1}^{na,U} \\ \beta_{it+1}^{na,U} \\ \alpha_{it+1}^{na,L} \\ \beta_{it+1}^{na,L} \end{pmatrix}$	$\hat{c}_{2i}^{na} > 0$	$\hat{c}_{2i}^{na} = 0$	$\hat{c}_{2i}^{na} < 0$

$\hat{c}_{1i}^{na} > 0$	$\begin{pmatrix} \alpha_{it}^{na,U} \\ \beta_{it}^{na,U} \\ \alpha_{it}^{na,c} \\ \beta_{it}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,U} \\ \beta_{it}^{na,c} + \frac{1}{2}\lambda_i^{na} \\ \alpha_{it}^{na,c} \\ \beta_{it}^{na,c} - \frac{1}{2}\lambda_i^{na} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,U} \\ \beta_{it}^{na,c} \\ \alpha_{it}^{na,c} \\ \beta_{it}^{na,L} \end{pmatrix}$
$\hat{c}_{1i}^{na} = 0$	$\begin{pmatrix} \alpha_{it}^{na,c} + \frac{1}{2}\lambda_i^{na} \\ \beta_{it}^{na,U} \\ \alpha_{it}^{na,c} - \frac{1}{2}\lambda_i^{na} \\ \beta_{it}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,U} \\ \beta_{it}^{na,U} \\ \alpha_{it}^{na,L} \\ \beta_{it}^{na,L} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,c} + \frac{1}{2}\lambda_i^{na} \\ \beta_{it}^{na,c} \\ \alpha_{it}^{na,c} - \frac{1}{2}\lambda_i^{na} \\ \beta_{it}^{na,L} \end{pmatrix}$
$\hat{c}_{1i}^{na} < 0$	$\begin{pmatrix} \alpha_{it}^{na,c} \\ \beta_{it}^{na,U} \\ \alpha_{it}^{na,L} \\ \beta_{it}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,c} \\ \beta_{it}^{na,c} + \frac{1}{2}\lambda_i^{na} \\ \alpha_{it}^{na,L} \\ \beta_{it}^{na,c} - \frac{1}{2}\lambda_i^{na} \end{pmatrix}$	$\begin{pmatrix} \alpha_{it}^{na,c} \\ \beta_{it}^{na,c} \\ \alpha_{it}^{na,L} \\ \beta_{it}^{na,L} \end{pmatrix}$
$\begin{pmatrix} \alpha_{jt+1}^{a,U} \\ \beta_{jt+1}^{a,U} \\ \alpha_{jt+1}^{a,L} \\ \beta_{jt+1}^{a,L} \end{pmatrix}$	$\hat{c}_{2j}^{a} > 0$	$\hat{c}_{2j}^{a} = 0$	$\hat{c}_{2j}^{a} < 0$
$\hat{c}_{1j}^{a} > 0$	$\begin{pmatrix} \alpha_{jt}^{a,U} \\ \beta_{jt}^{a,U} \\ \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,U} \\ \beta_{jt}^{a,c} + \frac{1}{2}\lambda_j^{a} \\ \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,c} - \frac{1}{2}\lambda_j^{a} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,U} \\ \beta_{jt}^{a,c} \\ \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,L} \end{pmatrix}$
$\hat{c}_{1j}^{a} = 0$	$\begin{pmatrix} \alpha_{jt}^{a,c} + \frac{1}{2}\lambda_j^{a} \\ \beta_{jt}^{a,U} \\ \alpha_{jt}^{a,c} - \frac{1}{2}\lambda_j^{a} \\ \beta_{jt}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,U} \\ \beta_{jt}^{a,U} \\ \alpha_{jt}^{a,L} \\ \beta_{jt}^{a,L} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,c} + \frac{1}{2}\lambda_j^{a} \\ \beta_{jt}^{a,c} \\ \alpha_{jt}^{a,c} - \frac{1}{2}\lambda_j^{a} \\ \beta_{jt}^{a,L} \end{pmatrix}$

$\hat{c}_{1j}^{a} < 0$	$\begin{pmatrix} \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,U} \\ \alpha_{jt}^{a,L} \\ \beta_{jt}^{a,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,c} + \frac{1}{2}\lambda_j^a \\ \alpha_{jt}^{a,L} \\ \beta_{jt}^{a,c} - \frac{1}{2}\lambda_j^a \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{a,c} \\ \beta_{jt}^{a,c} \\ \alpha_{jt}^{a,L} \\ \beta_{jt}^{a,L} \end{pmatrix}$
$\begin{pmatrix} \alpha_{jt+1}^{na,U} \\ \beta_{jt+1}^{na,U} \\ \alpha_{jt+1}^{na,L} \\ \beta_{jt+1}^{na,L} \end{pmatrix}$	$\hat{c}_{2j}^{na} > 0$	$\hat{c}_{2j}^{na} = 0$	$\hat{c}_{2j}^{na} < 0$
$\hat{c}_{1j}^{na} > 0$	$\begin{pmatrix} \alpha_{jt}^{na,U} \\ \beta_{jt}^{na,U} \\ \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,U} \\ \beta_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na} \\ \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,U} \\ \beta_{jt}^{na,c} \\ \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,L} \end{pmatrix}$
$\hat{c}_{1j}^{na} = 0$	$\begin{pmatrix} \alpha_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na} \\ \beta_{jt}^{na,U} \\ \alpha_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na} \\ \beta_{jt}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,U} \\ \beta_{jt}^{na,U} \\ \alpha_{jt}^{na,L} \\ \beta_{jt}^{na,L} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na} \\ \beta_{jt}^{na,c} \\ \alpha_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na} \\ \beta_{jt}^{na,L} \end{pmatrix}$
$\hat{c}_{1j}^{na} < 0$	$\begin{pmatrix} \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,U} \\ \alpha_{jt}^{na,L} \\ \beta_{jt}^{na,c} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,c} + \frac{1}{2}\lambda_j^{na} \\ \alpha_{jt}^{na,L} \\ \beta_{jt}^{na,c} - \frac{1}{2}\lambda_j^{na} \end{pmatrix}$	$\begin{pmatrix} \alpha_{jt}^{na,c} \\ \beta_{jt}^{na,c} \\ \alpha_{jt}^{na,L} \\ \beta_{jt}^{na,L} \end{pmatrix}$

The above will assist a buyer or seller in choosing the best bidding strategy variables based on rewards (if any) from the previous trading (simulation) round.

Appendix G **Factors Affecting Customer Forced Outages**

The following table shows the factors affecting forced outages in a location in North America for a major utility.

Table 6-12: Factors of Forced Outages

Birds
Trees, Fallen
Equipment Failure
Adverse Weather
Corrosion/Rot
Trees, Branch
Other
Unknown
Motor Vehicle Accident
Overload (Electrical)
Animals
Fire, Building, Brush
Customer
Trees, Growing Into
Vandalism
Lightning
Incorrect Installation
Construction
Unknown Cause
Vibration
Defective Transmission Line Equipment
Abnormal Voltage
Trees
Trees, Weekend Logger
Objects (Kites, etc.)
Defective Substation Equipment
Personnel Incident
Protection Setting Problem
Hydro Personnel Error
Salt Spray
Flood, Mud/Snow Slide
Dig-In (Cable)
Source Outage
Protection and Control
Industrial Pollution

Adverse Environment
Foreign Object
Snow / Ice / Freezing Rain
Station Breaker Failure
Other Cause
Overload
Operation Isolation
Wind
System Condition-Other
Undervoltage
Unbalanced Load
Defective Design
Local Control Setting
Incorrect Remedial Action Scheme Operation
Source (Transmission)
Remote Control Equipment Defective
Overvoltage
Overfrequency
Underfrequency