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Optimal Product Design Based upon Customer Requirements in One-of-a-Kind Production Environment

by

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled "OPTIMAL PRODUCT DESIGN BASED UPON CUSTOMER REQUIREMENTS IN ONE-OF-A-KIND PRODUCTION ENVIRONMENT" submitted by LILIN HU in partially fulfillment of the requirements for the degree of Master of Science.

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ABSTRACT

One-of-a-kind production (OKP) is a manufacturing paradigm for producing customized products while maintaining the scale of economy in mass production and a high standard of quality. In this thesis work, an optimal design approach for identifying the product that best satisfies the requirements of customer in performance and cost has been developed.

In this research, variations of OKP product configurations and parameters in a product family are modeled by an AND/OR tree. Customized product designs are created from the product family based on requirements of customers. A multi-level and multi-objective optimization method is developed for identifying the optimal design configuration and its parameters by using the evaluation measures of performance and cost specified by the customer. Since the different design evaluation aspects are usually modeled by different measures with different units, these measures are converted into comparable customer satisfaction indices through using the least-square curve-fitting method. Pair-wise comparison method is employed to achieve the weighting factors of the different evaluation indices. The configuration optimization and parameter optimization are conducted respectively through genetic programming and constrained optimization.

A prototype of the optimal OKP product design system has been developed through this thesis work by using Visual C++ based on the results achieved in the theoretical work. Several industrial case studies have also been carried out to demonstrate the effectiveness of the developed optimal OKP product design method.

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CHAPTER 1: INTRODUCTION

With the advances of science and technology, competition among manufacturing companies is becoming fiercer in the global market. To achieve a better place in the market competition, the manufacturing enterprises have to improve their manufacturing capabilities through shortening production lead time, reducing lifecycle costs, improving product quality, and providing better before- and after-sale services to meet the global market requirements driven by customers. In recent years, many new manufacturing paradigms and technologies have been developed and employed due to the advances of the other technologies, especially the computer technologies (Zhang and Xue 2001).

1.1 History of Production

Throughout the history of the manufacturing industry, various production systems and technologies have been developed and applied successively. Craft manufacturing is the earliest manufacturing mode. In craft manufacturing, products are manufactured by hands rather than by machines. Due to the industrial innovation that took place in England in the late eighteenth century, mass production has emerged as a major manufacturing method. Mass production resulted in a shift from home-based hand manufacturing to large-scale factory production, which greatly improved the efficiency of production. In recent years, mass customization, which aims at achieving both scale of economy and customization, was first proposed by Pine (1993) and was further studied and researched in many areas (Tseng and Du 1998, Tseng and Piller 2003). Meanwhile, One-of-a-Kind Production (OKP) paradigm and technology, which emerged in Europe and has been researched and developed to achieve the same goal as mass customization, has attracted the attention of many researchers (Tu 1997). However, mass customization researches have placed their emphasis on the business approach, such as e-commerce and web-based outsourcing management. One-of-a-kind production (OKP) focuses on the research and development of novel production systems, design methodologies and manufacturing technologies to achieve both scales of economy and customization. The research project presented in this thesis follows the approach of OKP.

1.2 One-of-a-Kind Production (OKP)

One-of-a-Kind Production (OKP) originated from heavy industries, such as ship building, steel construction, and boiler manufacturers, etc. where the products are designed and manufactured concurrently in terms of changeable customers' requirements. Over the past decades, OKP has been developed as a new manufacturing paradigm to be widely applied in other manufacturing companies across the world due to the requirements of customers on a high variety of products.

One-of-a-Kind Production normally means a particular production method by which a product (i.e., "One" in OKP) ordered by an individual customer within a specific product domain (i.e., "a Kind" in OKP) can be developed and produced (Tu 1997).

One-of-a-Kind Production, as a new production philosophy, is a typical production paradigm which can exactly convert the customers' requirements and development ideas into a specific product by a "once" successful approach with the constraints of production costs, design performance, production time, before- and after-sale services, delivery time, product quality, and so on.

1.3 Product Design and OKP

Due to the advances of computer communication and information technologies in the past decades, global competition is becoming the main characteristic of the market. To respond to the increasingly dynamic market requirements on developing new products, shortening the product development lead time and satisfying the customers' needs and requirements have become the driving force for the manufacturers to join the competition in the market. In product development, design is the major process that affects the performance of the product and has a significant impact on the downstream life-cycle phases of the product development process including manufacturing, assembly, operation, and recycle/disposal. The design idea and philosophy are the determinant factors that influence the quality and performance of the product. Therefore, more and more manufacturing enterprises have devoted more efforts in product design.

Design of OKP products also plays a key role in OKP manufacturing companies to improve the quality of products and satisfaction of customers. In recent years, some of the OKP manufacturing companies have devoted great efforts on product design and optimization according to the requirements from the customers to meet the fiercer competition environment in the global market (Tseng and Piller 2003).

For OKP product design, both the characteristics of OKP products and design technologies should be considered at the same time. Therefore, theoretical studies on design of OKP products are required.

In the following sections of this chapter, problems encountered in OKP product design and the methodologies for identifying the optimal design of OKP products will be discussed. Thereafter, the objectives of this thesis research work are outlined and the research methodology is presented.

1.4 Problems in OKP Product Design

A number of issues need to be addressed to design products in one-of-a-kind production environment. These issues are summarized as follows.

(1) Modeling of OKP products

The first step in OKP is to design the optimal product based on the requirements from customers usually in terms of functional performance and production costs. This OKP product is usually created as a special one in a family of OKP products through customization. Therefore, modeling of the generic OKP product families and creation of OKP products based on the requirements of individual customers are required.

(2) Evaluation of OKP products

Since any OKP product is a special one in a family of OKP products, many of the products in this family could satisfy the given customer requirements. Evaluation of different products based on the requirements of customers, therefore, is required to identify the optimal product design that best satisfies the customer requirements. Two issues need to be addressed for evaluating product design in OKP. One is to achieve the evaluation measures of the product, such as functional performance, production cost, operation cost, maintenance cost, etc. The other is to associate these evaluation measures with customer requirements.

(3) Identification of the optimal design in OKP

Variations of products in OKP include configuration variations (e.g., an LCD monitor verses a plasma monitor) and parameter variations (e.g., a 21-inch monitor or a 9-inch monitor). Due to the large variation of product configurations and parameters, efficient and effective optimization methods are required to identify the optimal product configuration and parameters based on the evaluations of these product configurations and parameters.

1.5 Research Objectives and Methodologies

This thesis work addresses the problems given in Section 1.4 by developing a new approach to identify the optimal design configurations and parameters under the considerations of the customer requirements on performance and costs.

1.5.1 Research Objectives

The objectives of this research are identified based on the extensive studies on the activities of one-of-a-kind production in OKP companies, especially Gienow Windows and Doors at Calgary, Canada. The research objectives are summarized as follows.

(1) Development of a new scheme to model variations of OKP product configurations and parameters

Variations of products include variations of configurations and variations of parameters. For example, internal hard drive and external hard drive of a computer are two different configurations, while the size and the access speed are two parameters of the hard drive. In the traditional OKP database, both the variations of configurations and variations of parameters are modeled in the same way. Since a product is first modeled by its configuration, and parameters are associated with this configuration, a new database representation scheme to model both the variation of configurations and variation of parameters are required.

(2) Modeling of relations between products and their evaluation measures based on customer requirements

In OKP environment, different product configurations and parameters are evaluated by different evaluation measures of customers including performance measures (e.g., power output and efficiency) and cost measures (e.g., product cost and maintenance cost). Since performance and cost measures are usually defined with different units, a method to convert these evaluation measures into comparable measures and to integrate these measures to model the overall customer satisfaction is required for solving this multi-objective optimization problem.

(3) Identification of the optimal product configuration and its parameters through multi-level optimization

Since both the variations of configurations and the variations of parameters are modeled in the same manner in the traditional OKP database, the optimal product is usually identified by treating the variations of configurations as discrete variables and the variations of parameters as continuous variables. Since the product configurations and parameters should be modeled at the different levels, a new optimization method to achieve the optimal product configuration and its parameters at different levels is needed.

1.5.2 Research Methodologies

To achieve the research objectives given in Section 1.5.1, a new OKP product design method is introduced in this research for identifying the optimal product configuration and its parameters considering the different customer requirements on performance and costs.

(1) Modeling of product configuration variations and parameter variations using an AND/OR tree

In this research, variations of product configurations are modeled by an AND/OR tree. Each node in the AND/OR tree models partial product descriptions. When a node is supported by all the sub-nodes, these sub-nodes are associated with a logic AND relation. When a node is optionally supported by only one of its sub-nodes, these sub-nodes are associated with an OR relation. Each functional node is associated with a number of parameters. Different feasible product configurations are created from the AND/OR tree. Each product configuration is modeled by a number of nodes with parameters.

(2) Modeling of the relations between products and their evaluation measures

Different evaluation measures, including performance measures and cost measures, are modeled as functions of product configurations and parameters. To associate these evaluation measures with different units, these evaluation measures are first converted into evaluation indices based on customer satisfaction. Since the relations between evaluation measures and evaluation indices are usually non-linear relations, these relations are modeled using cubic polynomial functions. The least-square curve-fitting method is employed to achieve the cubic polynomial functions from the selected evaluation measures and their corresponding satisfaction indices. These evaluation indices, modeled with values between 0 and 1, are associated by weighting factors representing the importance of these evaluation aspects based upon customer requirements. When the number of evaluation measures is big, pair-wise comparison method (Satty 1980) is employed to keep the consistency of these weighting factors. When these different evaluation measures are considered as objective functions for identifying the optimal product, this multi-objective optimization problem is then converted into a single-objective optimization problem considering these weighting factors.

(3) Identification of the optimal product configuration and parameters using multi-level optimization approach

Since variations of products include variations of configurations and variations of parameters, optimization is also conducted at two different levels: the configuration level and the parameter level. In this work, genetic programming (Koza 1992) and constrained optimization (Arora 1989) are employed for configuration optimization and parameter optimization respectively. A generation of configurations is first created and the optimal parameters of each configuration in this generation are identified using parameter optimization. Three genetic programming operators, reproduction, crossover, and mutation, are then used to generate a new generation of configurations. Since the configurations with better evaluation measures in the previous generation have better chances to be used for creating the configurations in the next generation, the average quality of the configurations in the next generation is usually better. This evolution process is continued until quality improvement cannot be further achieved.

(4) Development of a computer-aided optimal OKP product design system using the multi-level and multi-objective optimization approach

A computer system has been developed based on the theoretical results achieved in this research. In this system, variations of product configurations and parameters are modeled using an AND/OR tree. The different product evaluation measures are associated with different evaluation indices and their weighting factors normally in non-linear relations among these evaluation measures. The optimal product configuration and its parameters are identified through a multi-level multi-objective optimization approach (Xue 1997). The system was implemented by using Visual C++ 6.0.

1.6 Organization of This Thesis

This thesis is organized in six chapters, as shown in Figure 1.1.

Chapter 2 begins with a detailed literature review that provides the background of this research work. This literature review covers the major topics related to this research. These topics include engineering design and relevant technologies, one-of-a-kind production approach, design in OKP environment, etc. The computing techniques employed in this work, including AND/OR tree modeling, multi-objective design optimization to identify the best solution, and the evolutional computing methods of genetic algorithm and genetic programming, are also explained in this chapter. In addition, OKP activities at a local manufacturing company, Gienow Windows and Doors Ltd., are also introduced in this chapter.

Chapter 3 first presents the method to model variations of OKP product configurations and parameters using AND/OR trees. Modeling of customer requirements is then provided in this chapter. Modeling of the non-linear relations among different product evaluation measures is subsequently discussed. The least-square curve-fitting method is first used to model the non-linear relations between the evaluation measures and the

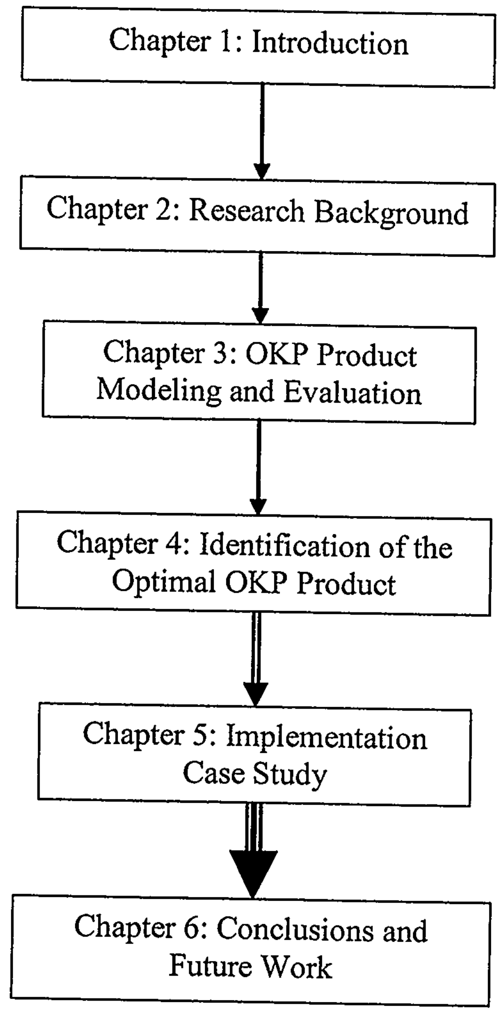


Figure 1.1 Structure of this thesis

evaluation indices. The pair-wise comparison method is then employed to obtain the weighting factors of the evaluation measures for converting the multi-objective optimization functions into a single-objective optimization function.

Chapter 4 focuses on the methods for identifying the optimal product configuration and its parameters using multi-level optimization approach. The optimization is conducted at two different levels: configuration level and parameter level. Genetic programming is employed to identify the optimal configuration from the AND/OR tree. Parameter optimization is employed to achieve the optimal parameters of the product configuration. In this research, constrained optimization is used to obtain the optimal parameter values.

Chapter 5 provides the details of system implementation and case study examples. In this research, customized window products at Gienow Windows and Doors are used as OKP products. Modeling of windows using AND/OR tree, modeling of the non-linear relations between product evaluation measures and evaluation indices based upon customer requirements, and identification of the optimal window product configuration and parameters using the multi-level and multi-objective optimization method are also presented in this chapter.

Chapter 6 draws the conclusions of this thesis research work. Limitations and future work are also included in this chapter.

CHAPTER 2: RESEARCH BACKGROUND

This chapter presents a general literature review on the subjects relevant to the research introduced in this thesis. These subjects include engineering design, one-of-a-kind production, AND/OR tree, multi-objective optimization, and genetic programming. A brief introduction to Gienow Windows and Doors Ltd., which is a typical OKP company in Calgary, is also provided at the end of this chapter.

2.1 Literature Review

2.1.1 Engineering Design

Product design is a complex process that involves human intelligence and available techniques. Among the different product development activities, product design is considered the most important activity in the product development process. Engineering design is usually conducted through a series of stages, including acquisition of design requirements, identification of technical specifications, creation of design candidates, determination of design parameters, documentation of engineering drawings, and so on. Following the conventional approach of product design, the design processes are sorted into three sequential design phases, i.e. conceptual design, embodiment design, and detailed design (Nunua 1995).

2.1.1.1 Design and Design Process

Among many definitions of design, Takala (1989) defined design as "the process of finding or constructing a product or its explicit representation, or model of it, which will implicitly satisfy specified functional and other requirements expected by its users." This definition of design has been widely recognized in the modern design world. In Europe, the word "design" often has a different connotation, more artistic and less technical, perhaps inherited from its origins (Jiao and Tseng 2004). According to Orel (1991), the concept of design was introduced during the Renaissance period. When artists were talking about design, this word would be used to describe the quality of a model or picture.

The process of design has also been considered to play a key role in transforming design requirements into design solutions. Treur (1991) stated: “In general a design process starts by establishing the need for a certain object and by expressing a number of properties that the object should possess. These properties are called the (initial) design requirements. The aim of a design process is to construct an explicit description of the structure of an object satisfying the design requirements.”

Conceptual design is the first design phase to identify the basic principles of the design. In conceptual design, many design candidates could be created and the best one is selected based on the initial evaluations to these candidates. Detailed design provides the detailed design descriptions, including dimensions and tolerances, which are missing at the stage of conceptual design.

Many researchers have tried to define conceptual design over the past years. McNeil et al. (1998) defined conceptual design as the earliest phase of the design process which is distinguishable from the later phase in that it is concerned more with the understanding of problem and making general rather than specific decisions about the solution. McNeil et al. (1998) also stated: “Conceptual design comments with high level descriptions of requirements and proceeds with a high level description of a solution.”

2.1.1.2 Configuration Design

Configuration design is defined by Carlson-Skalak and his colleagues (1998) as: “the engineering task in which a configuration is created by assembling off-the-shelf components into a functional system.”

A configuration is actually created by combining different components based on the functions of these components. The main task in configuration design is to select the existing components based on the requirements of functions and to create a product for satisfying the requirements of the customers. Many methods have been developed for creating design configurations based on design requirements.

Mcdermott (1982) developed a method of "reasoning about the function of a component eventually abstracted at different levels". Sun et al. (2000) used neural network-based fuzzy reasoning to achieve the configuration of the product. Xue (1997) employed genetic algorithm and genetic programming to search for the configuration based on the existing product models.

In OKP design, a product family is first modeled by variation of product configurations. Each product configuration is associated with design parameters. The performance and cost of customer requirements are primarily determined by product configurations. Therefore modeling of product configurations and identification of the optimal configuration play important roles in OKP product design.

2.1.1.3 Parameter Design

In the mid 1980s, parametric design was introduced in the commercial CAD systems. In parametric design, the dimensions are modeled by variables. Constraints among geometric elements, such as the numerical relations between two dimensions and parallel relations between two surfaces, can also be defined in parametric design. Many constraint solving methods and tools have also been developed for parametric design (Xue and Dong 1998).

In mechanical design, usually a feasible configuration is created first. The parameters of this configuration are then determined based upon the design objectives and constraints.

Because the parameter design is usually conducted by considering various constraints of design, constrained optimization method is an effective method to achieve the optimal design parameters within the allowable ranges of the variable values. During the search process, multiple objectives sometimes need to be considered. Multi-objective methods are employed when multi-objectives are considered in parameter design (Yang et al. 2005). More discussions on multi-objective optimization will be given in Section 2.2.3.

2.1.1.4 Concurrent Engineering Design

The lifecycle of a product development usually consists of many phases, including conceptual design, detailed design, design analysis, production process planning, machining, assembly, inspection, delivery, maintenance, etc. To compete with other companies' products in the global market, more and more manufacturing companies have incorporated considerations in the downstream product development phases into the early design stage. The design method considering downstream product development aspects is called concurrent engineering design or concurrent design (Kusiak 1993). Concurrent design can better satisfy customer requirements by improving product manufacturability and reducing production cost to improve competitiveness of products in the global market. Concurrent design is sometimes called cooperative design, collaborative design, or interdisciplinary design when many parties of the product development team, including manufacturing engineers, marketing personnel, etc., are involved in the design process (Frutos et al. 2004).

In concurrent design, various product development aspects, including manufacturing, assembly, test, quality, purchasing, and so on, should be considered simultaneously. The main objective of concurrent design is to shorten the product development time, improve the production efficiency, improve the product quality, shorten the delivery time, shorten the lead time to the market, minimize the product cost, reduce the maintenance cost, etc. Effectiveness of concurrent design has been widely recognized by industrial companies to improve the competitiveness of their products. Kohili and Forgionne (1992) have briefly summarized the benefits that concurrent engineering has given to the manufacturing companies: development and production lead times; measurable quality improvements; engineering process improvements; cost reduction, etc.

With the fast development of computer technology, computer-aided design (CAD) has been widely used in concurrent design (Zhang and Xue 2002). Feature recognition is an approach to extract the geometry to be produced from the CAD database for planning design and manufacturing process (Henderson 1984). Most of the developed concurrent design systems focus on only one of the down-stream product development life-cycle aspects, including manufacturing, assembly, maintenance, recycle/disposal, and so on (Kusiak 1993, Prasad 1996).

The computer-aided concurrent design approach is employed in this research to identify the optimal design configurations and parameters considering performance and costs.

2.1.2 Customization and Mass Customization

To improve the competitiveness of products, the products have to better satisfy requirements of customers. Although mass production can satisfy requirements of customers by reducing product costs, it provides limited selections of products to satisfy different needs of individual customers.

Product customization is the company's capability to satisfy various needs of customers by economically changing its products or services (Xie et al. 2004). It has been recognized as one of the main focuses in product design and manufacturing (Kidd 1994). Meredith and Francis (1998) believed that an appropriate product design according to customer requirements was able to make a product almost at the same unit cost while significantly improving the customer satisfaction. It has been shown that customization could play a key role in improving the product popularity.

Mass customization is another term that has been widely used to note the mass production of customized or OKP products. Tseng and Du (1998) characterized mass customization as recognizing each customer as an individual, meanwhile extracting maximum commonality to achieve scale of economy. The main goal of mass customization is to deliver products and services that best reflect the actual choices of individual customers based on their needs and preferences (Frutos et al. 2004).

To implement the customization theory into the manufacturing and design of products, many researchers have been involved in research on mass customization. The typical achievements among these research efforts would be the so-called design for modularity (Exixon 1996, Marshall and Leaney 1999), variant design (Fowler 1996, Mckay et al. 1996), and design for manufacture (Gupta et al. 1997, Chen et al. 1998), design for production management planning (Alting and Zhang 1989, Wu and Zhang 1998, Tu et al. 2000). However, most of these methods could only solve partial customization problems. For the highly customized OKP products, the above methods cannot meet the detailed requirements.

In some industries, such as the industry of building products including doors and windows, customized products have to be manufactured based on the requirements of individual customers. Usually the requirements of customers are first identified by the salespersons. These requirements are then converted into engineering requirements to design and manufacture the products to satisfy the needs of customers. Since each product is designed and manufactured differently, the cost of product is higher than the cost of the product through mass production.

With the advances of computer technologies, many of the design and manufacturing activities have been automated by computer systems. A new manufacturing approach, called mass customization production, has been introduced and developed in the recent years to manufacture customized products with the quality and efficiency of mass production (Tseng and Piller 2003). In the research on mass customization, Davis (1987) and Pine (1993) defined mass customization as a business strategy that involves customers in the development process of a product in order to address individual customer needs. Mass customization method has also been employed in manufacturing industries to improve the varieties of products (Jiao and Tseng 2004).

Currently, the research of mass customization focuses on the business strategies by providing varieties of products using Internet technologies (Tu et al. 2005). To address the design and manufacturing issues, the One-of-a-Kind Production (OKP) approach was introduced by Wortmann (1989).

2.1.3 One-of-a-Kind Production

In the history of production, different types of production methods have emerged, such as craft production, job shop production, mass production, batch production, one-of-a-kind production, etc.

Craft production was the earliest production form when machines were not invented. In craft production, the products were made by hands. After the industrial revolution in the late eighteenth century, the use of machines resulted in a shift from home-based craft production to large-scale factory production. The large-scale factory production developed and adopted so called mass production which can produce large volumes of products in a high efficiency and hence reduce the manufacturing costs significantly.

Nowadays, due to the dramatic increase of customization and global competition, manufacturing companies need to produce customized products with high quality at a competitive price. To achieve this goal with the limited available resources in a manufacturing company has become one of the main tasks for a wide range of manufacturers to survive and further develop in the market. To meet this challenge, one-of-a-kind production paradigm is becoming more and more popular in manufacturing companies, particularly in small and middle sized manufacturing enterprises.

As aforementioned in this thesis, one-of-a-kind production (OKP) normally means a particular production method by which a product (i.e., 'One' in OKP) ordered by an individual customer within a specific product domain (i.e., 'a Kind' in OKP) can be developed and produced (Tu 1997). OKP, as a new production philosophy, also means a particular production method, which can convert the customers' requirements, needs and development ideas into a product by a 'once' successful approach under constraints of critical delivery date, cost, and quality.

Table 2.1 summarizes the characteristics of three typical production methods (craft production, mass production, and one-of-a-kind production).

Table 2.1 Summary of craft production, mass production and OKP

Item \ Type	Craft production (CP)	Mass production (MP)	One-of-a-kind production (OKP)
Flexibility	High	Low	High
Quality	Low	Standard Quality	High
Product variety	High	Low	High
Cost/Price	High	Low	Low
Efficiency	Low	High	High
Volume	Low	High	High
Inventory	Low	High	Low
Customer influence	High	Low	High
Customization	High	Low	High
Character	Low availability of customized goods and services	High availability of standard goods and services	High availability of customized goods and services
Example	Pre-Industrial Revolution	Ford	Dell

From Table 2.1, we can see that one-of-a-kind production has both advantages of craft production and mass production. It is a kind of production with high quality, high flexibility, low inventory, high efficiency, low cost, large volume, and high customization. Apparently, OKP has many more advantages over other two types of production. In the table, Ford and Dell are respectively given as examples of mass production and one-of-a-kind production.

In recent years, great efforts have been devoted on the clear definition and complete description of problems in OKP (Tu 1997). Wortmann (1989) has created an OKP typology by two dimensions. One dimension concerns the two types of production systems: product-oriented systems and capability-oriented systems. The other dimension concerns with the four general market competitive strategies: make to stock, assemble to order, make to order and engineer to order. Different kinds of one-of-a-kind production have their own specific characteristics, and these different characteristics are shown in Table 2.2 (Wortmann 1992). Hirsch et al. (1992) summarised the characteristics of OKP as: simultaneous production, customer influence over the whole production, autonomous production area, inter-organizational production, relevance of quotation planning, and incomplete product and process data.

Table 2.2 Characteristics of different types of OKP production

Category / Characteristic	Engineer to order	Make to order	Assembly to order	Make to stock
Management level focuses on:	Customer order contacts	Capacities	Innovation	Marketing and distribution
Uncertainties mainly exist in:	Product specifications	Product processes	Mix of order	Product life-cycle
The main complexity exist in:	Engineering	Components manufacturing	Assembly	Physical distribution
The information systems focus on:	Support of product engineering	Support of manufacturing engineering	Support of material supply and order entry	Support of forecasting and stock control

In Tu (1997), the characters of one-of-a-kind production have been also summarized as follows:

- High customization;

- 'Once' successful approach on the product;
- Optimal or rational utilization of technologies and resources;
- Adaptive production planning and control;
- Continuous customer influence through the production process;
- Prototype-based evolutionary and concurrent approach of product development and production;
- Distributed control and inter-organizational autonomy; and
- Virtual company structure and global manufacturing.

In recent years, one-of-a-kind production approach has been recognized and used in the manufacturing industries, especially in the small and medium sized manufacturing companies. According to statistics, nearly 85 percent of the manufacturing companies in Canada are small and medium sized manufacturing companies. The development of a systematic approach for OKP product design and manufacturing will play an important role in improving the competitiveness of the products of the small and medium sized manufacturing companies.

By employing the OKP design approach, the manufacturing companies can shorten product development lead time, increase product diversity, improve product quality, and reduce production costs, thus better satisfying requirements of the customers.

Among various issues to be addressed in OKP product development, OKP product design plays an important role. Therefore, this research primarily focuses on the design issues in OKP environment.

2.1.4 Design in OKP

Due to the high level of customization of OKP products, design and manufacturing of these OKP products are conducted differently. Therefore, the product development costs are usually higher and the lead times are usually longer compared with mass production. To reduce the cost and lead time, sophisticated computer systems have to be developed to create different designs based upon customer requirements and to generate manufacturing processes for achieving these designs. Since 85% of the product cost is determined at the design stage, great efforts have been devoted to identify good designs in the past decades (Prasad 1996).

Through an intensive study on the activities of OKP product development, the following issues should be considered in OKP product design. First, an OKP product modeling scheme has to be developed. Since OKP products are usually grouped into product families, modeling of product families with variations of design configurations and design parameters is required. Second, creation of design candidates from a product family and evaluation of these candidates should be conducted. Since requirement of a customer can usually be satisfied by numerous design candidates, an optimization approach is required to identify the optimal design configuration and parameters to best satisfy the requirement of the customer.

Sophisticated computer systems need to be developed for OKP product design and manufacturing. The following functions should be provided in the OKP design and manufacturing systems (Xie et al. 2004):

- The system should have a flexible and open structure to meet the flexible needs from customers.
- The system should support the integration of enterprises and organizations.
- The system should support the cooperation and collaborations among the different departments of the enterprises, and among the enterprises and the customers.
- This system should support the high customization.
- The system should use the existing database of the enterprises if that database is available already.
- The system should be compatible with most existing product development software tools.

2.2 Techniques Used in This Research

To solve the OKP product design problems as mentioned in the previous sections, some relevant techniques have been used in this research for developing the new OKP product design method. These techniques include AND/OR trees for product modeling, multi-level optimization for identifying the optimal design configuration and its parameters, multi-objective optimization considering different design evaluation measures such as performance and costs, and genetic programming for improving the quality and efficiency of optimization.

2.2.1 Product Modeling and AND/OR Trees

2.2.1.1 Product Modeling

The following components should be provided for product modeling (Xie et al. 2004):

(1) Entities:

An entity is a construction that represents the appearance in the real world. It should be based on the real manufacturing or real design world, and match with the reality.

(2) Properties:

A property specifies a characteristic of an entity. Properties should be able to represent numerical values, constraints, and behaviours. In this element, some values or parameters should be contained here, so that when the model is constructed, the relevant parametric characters are defined. Attributes are special properties for modeling quantitative information of products.

(3) Relations:

Design entities are associated by relations. These relations include implicit relations (e.g., certain attributes forming a constraint) or explicit relations (e.g., an attribute defined as a function of other attributes).

A product model should contain a large amount of data, information and knowledge. Various design and manufacturing activities should be described by this model. Customer requirements should also be described by this model. When these different product aspects are not well integrated, many iterations of redesign and remanufacturing are required to meet the requirements of the customers. This will lead to long product development lead time, low customer satisfaction, and poor competitiveness in the market. In this research, an AND/OR tree is used to model the OKP product.

2.2.1.2 AND/OR Tree

The AND/OR trees have been widely used in artificial intelligence. Nilsson (1971) considered the AND/OR tree as an appropriate way to describe the hierarchical relations among the entities. A hierarchical system can be decomposed in a top down fashion into sub-systems, sub-sub-systems, and so forth.

Figure 2.1 illustrates the concept of AND/OR tree. In this tree, the node *W* is the root node. There are two kinds of relations among the sub-nodes of a parent node: 'AND' relations and 'OR' relations. For example, the node *M* has two sub-nodes, *Z3* and *Z4*, with an 'AND' relation. The node *Y* has two sub-nodes, *Z1* and *Z2*, with an 'OR' relation.

Many trees with only 'AND' relations can be created from the AND/OR tree for representing different alternatives. If the sub-nodes of a parent node are associated with an 'AND' relation, when the parent node is selected for creating an alternative, all these sub-nodes should be selected. For instance, if the node *M* is selected, all the sub-nodes of *M*, *Z3* and *Z4*, should be selected. The top node is called a root node. The bottom nodes are named leaf nodes. As shown in the Figure 2.1, *W* is a root node, while *Z1* is a leaf node. Therefore, we can get a conclusion that if we want to create a configuration from an AND/OR tree, we should check all the nodes from the root node to leaf nodes. If a parent node has sub-nodes with an 'OR' relation and this parent node is selected for creating an alternative, only one of the sub-nodes need to be selected. For instance, if the node *X* is selected, one of its sub-nodes, either *M* or *N*, should be selected for creating an

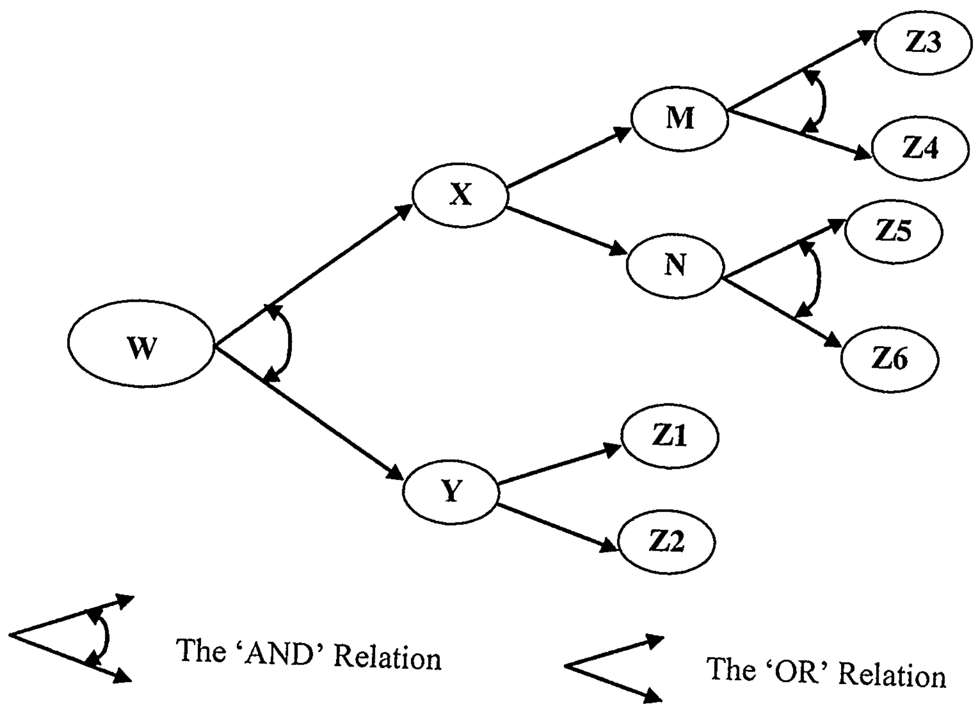


Figure 2.1 An example of AND/OR tree

alternative. Four alternatives have been created from the AND/OR tree given in Figure 2.1. These four created alternatives with only AND relations are shown in Figure 2.2. The four alternatives are ***Individual_a***, ***Individual_b***, ***Individual_c***,and ***Individual_d*** generated from the example AND/OR tree in Figure 2.1. The nodes in an AND/OR tree can be used to describe components and assemblies of a product. Each node can be associated with parameters representing the attributes of the components such as dimensions and tolerances. From an AND/OR tree for modeling the variations of product, many design alternatives with only AND relations can be created. These design alternatives are called *design configurations* in this research. Each design configuration is described by a set of *design parameters*.

An AND/OR tree is built to model the product family based on the functions and structures of the products. The parameters of the nodes can be modeled by continuous parameters, discrete parameters, integer parameters, and Boolean parameters. In engineering design, alternative design configurations are first created. Since each design

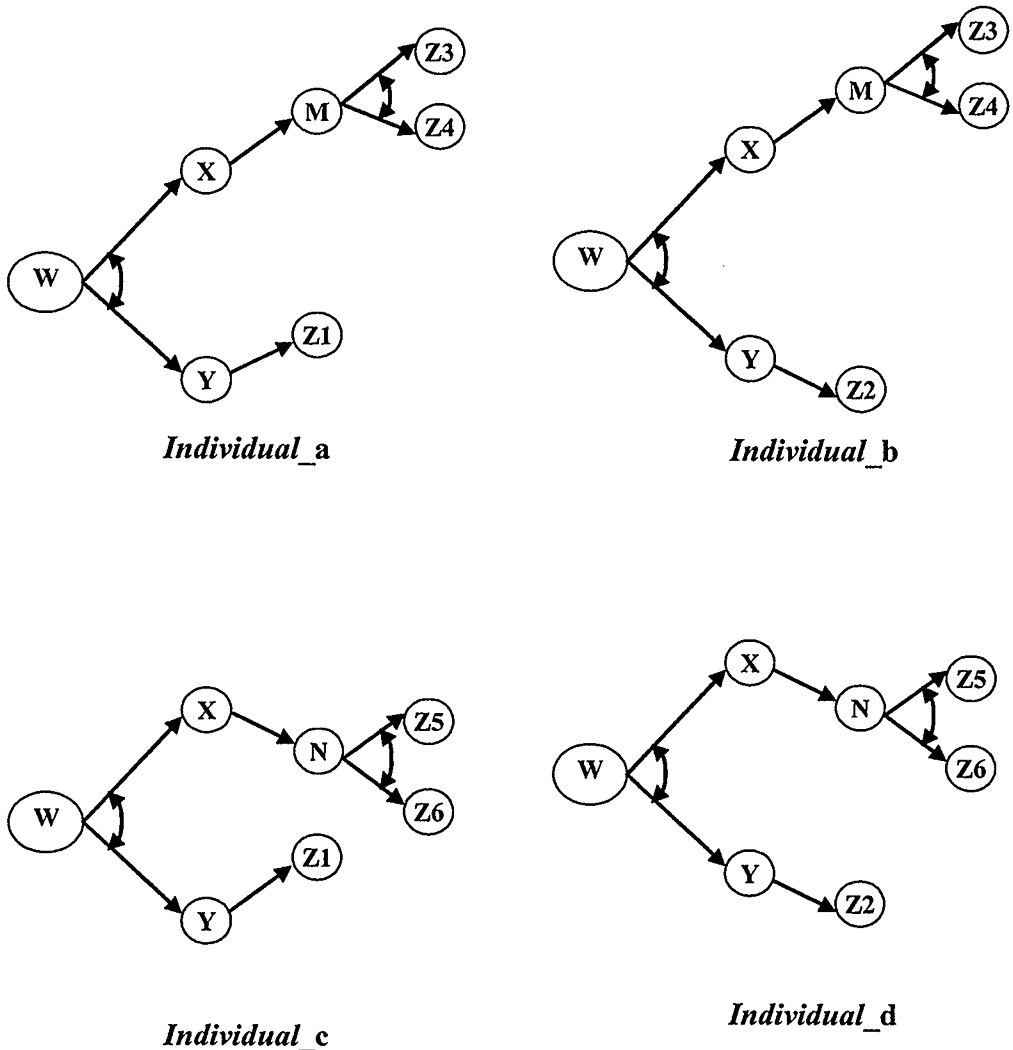


Figure 2.2 Four alternatives created from the AND/OR tree

configuration is modeled by design parameters, values of these parameters are then identified. A design result is described by both the design configuration and the parameters of this configuration.

2.2.2 Multi-level Optimization

Xue (1997) introduced the multi-level optimization approach considering product realization process alternatives and parameters of these alternatives to improve manufacturability of the products. In Xue' research, optimization is conducted at different levels for identifying the optimal results at these different levels.

Multi-level optimization method is also used in this research. Two-level optimization is conducted for identifying the optimal design: configuration optimization and parameter optimization. The configuration optimization is a process to identify the optimal configuration considering all possible product configurations. At this level, the genetic programming (Koza 1992) is employed to identify the optimal configuration. The parameter optimization is a process to reach the specific parameters of the different configurations which are created in the process of the configuration optimization. The parameter optimization in this research is formulated as constrained optimization. Because multiple life-cycle aspects of a product are considered at the same time, and some of these aspects are in conflict each other, a multi-objective optimization method is used to reach the best product with the appropriate parameters considering these life-cycle aspects based on the requirements of customers.

An algorithm with three steps was introduced to identify the optimal product from product model (Xue 1997):

Step 1. Generate a new feasible configuration from the product family model.

Step 2. Optimize the parameters of the selected configuration.

Step 3. Use the results obtained in the second step to evaluate the configuration. Terminate the optimization process if the optimal configuration and its parameters have been identified. Otherwise go to the first step again to repeat the process.

In this research, the multi-level optimization theory is employed to identify the optimal configuration and its parameters based on the product modeling with the AND/OR tree introduced in the previous sections of this chapter.

In OKP production, MUSYK project (ESPRIT 1993) developed an integrated multi-level control system for one-of-a-kind production. It aimed at providing support for production planning and control in OKP environment. In MUSYK project, multi-level control method was used to develop the production control system. In this research, multi-level optimization method is employed to identify the optimal product design from the OKP product family.

2.2.3 Multi-objective Optimization

In past years, many methods have been developed to improve the manufacturability of the products. These methods include axiomatic approach (Suh et al. 1978), feature extraction and evaluation approach (Priest and Scachez 1991), constraint network approach (Young et al. 1992), and so on. Since different life-cycle aspects, including design and manufacturing, are considered, multi-objective optimization approach is usually used for identifying the design for improving manufacturability while maintaining high design performance.

Optimization is defined in the English dictionary as "the procedure or procedures used to make a system or design as effective or functional as possible with mathematical techniques involved". Optimization is often used in design to identify the best design result to achieve a pre-selected design objective such as functional performance or production cost. With the advances of computer technologies, many optimization algorithms and tools have been developed for improving the efficiency and quality of engineering optimization.

When only one goal needs to be reached, the optimization problem is called a single-objective optimization problem. When multiple objectives are considered, the optimization problem is then called a multi-objective optimization problem. In engineering design, since multi-objectives, such as functional performance and production cost, need to be considered, multi-objective optimization is widely used for identifying the optimal design considering these design objectives.

In multi-objective optimization, the different objectives sometimes conflict with each other. For example, several objectives have to be considered when the customer's satisfaction needs to be improved. These objectives include lowering the cost, improving the quality of the product, shortening the production time, reducing the delivering time, etc. It is important to find a design solution with low cost while maintaining the quality of the product. There is a trade-off among these objectives to be reached.

Multi-objective optimization is an effective approach for solving the multi-objective design problems. It is an effective way to find the trade-off among the various design evaluation measures (Roman et al. 1995). Especially with the advances in concurrent design, there are so many design measures to be considered in different product life-cycle aspects, such as functional performances, costs, etc., for obtaining the optimal design considering the whole product life-cycle performance (Kusiak 1993, Prasad 1996).

A multi-objective optimization can be defined as:

$$Min\ F(X) = \{f_1(X), f_2(X), \ldots, f_m(X)\} \tag{2.1}$$

subject to:

regional constraints: $X_L \leq X \leq X_U$

inequality constraints: $G_j(X) \leq 0, j=1, 2, \ldots, p$

equality constraints: $H_k(X)=0, k=1, 2, \ldots, q$

where $X=(x_1, x_2, \ldots, x_n)$ is a vector with n optimization parameters, $x_1, x_2, \ldots, x_n$. These optimization parameters could be continuous variables, discrete variables, integer variables, and Boolean variables. $f_i(X), i=1, 2, \ldots, m$ is an objective function. Usually there are more than one objective functions to be optimized at the same time.

In real engineering design world, the design problems usually have many conflicting objectives, so multi-objective optimization method is widely employed in engineering design. Presently, multi-objective optimization approach has been widely employed in different types of engineering design and manufacturing, such as decision-based design

(Mistree et al. 1993, Chen et al. 1998), and different types of engineering applications such as fuel cell application (Wang and Shan 2004).

The multi-objective optimization could be primarily classified into three categories (Wang and Shan 2004). The method in the first category converts a multi-objective optimization problem into a single-objective optimization problem by assigning weights, preferences, utilities, or targets to the different objective functions (Ponnambalam et al. 2004). The methods in the second category are used to first identify the multiple Pareto set points (i.e., the optimal solutions) and then let the decision makers to select one based upon their selection criteria (Farmani et al. 2005). The methods in the third category try to model each single objective function and then explore the Pareto optimal frontier by using surrogate models or directly approximating the Pareto optimal functions (Li et al. 1998).

The multi-objective optimization method developed in this research belongs to the first category. The following steps are used to identify the optimal design considering multiple design objectives:

- The first step is to model each single objective of the design. In this thesis work, every single objective function could be achieved according to the requirements of customers. This objective function is modeled using relevant design parameter variables.

- The second step is to find a way to integrate the different objectives into one objective. In this step, various design evaluation measures are converted into customer satisfaction indices, and these indices are associated with weighting factors.

- The last step is to identify the optimal design using the overall objective function achieved in the second step. Various computing techniques are used for identifying the optimal design, including the optimal design configuration and its optimal parameter values.

2.2.4 Genetic Programming

Product design is a complex process that involves considerable knowledge and decision-making. Some techniques in Artificial Intelligence (AI), such as expert system, fuzzy logic, neural network (Lehne et al. 1991), etc., have been applied in computer systems to improve product development capability. In this research, genetic programming (Koza 1992) is employed to identify the optimal solution based upon the feasible design configurations created from the product model described by an AND/OR tree.

2.2.4.1 Genetic Algorithms (GAs) and Genetic Programming (GP)

Genetic algorithms were invented by John Holland in the early 1970's, and John Holland is called the father of the Genetic algorithms (Koza 1992). Genetic algorithms are adaptive heuristic search algorithms through using the evolutionary ideas of natural selection and genetics. GAs simulate the survival of the fittest among individuals over consecutive generation for solving the problem.

Genetic programming was developed based upon genetic algorithms. Genetic programming is an adaptive learning approach based on many of the principles of genetic algorithms (Zongker 1995). For both of GAs and GP, alternative solutions of a problem are represented as different individuals to form a population. Fitness value is a number, which indicates how good an individual solution is to the problem (Koza 1992). Populations are refined by choosing best individuals, breeding and moving individuals to next generations. The weakest individuals will disappear from the individual family. Populations will be modified up to a pre-determined number of generations or until a given fitness value is reached. Both of GAs and GP follow the theory of Charles Darwin, which is called 'survival of the fittest'.

GAs and GP share the same principle. Genetic programming was developed based on the genetic algorithms. However, there are some differences when they are employed to solve optimization problems.

Standard genetic algorithms use a fixed length representation of solution. Usually a solution is described by a binary code, although alphabet coding is allowed. On the contrary, genetic programming uses a data structure with variable length, such as a tree, for modeling an optimization solution. It is clear that both GAs and GP are related as they are both inspired by Darwinian evolution theory.

2.2.4.2 Genetic Operators

For GAs and GP, they both are based upon an analogy with the genetic structure and behaviour of chromosomes within a population of individuals. The basic foundations are:

- The reason why the individuals in the same population compete with each other is that they all want to survive and develop for resource or mates.
- For the stronger or successful individuals in a population, they will have more opportunities to produce their offspring. On the contrary, the poor individuals will have less offspring than the stronger ones.
- Usually, the two stronger or more successful parent individuals will produce better child individuals than the poor parent individuals due to the better "gene".
- With the genetic process going on, the individuals will be getting better and better generation by generation.

To get the optimal individual or improve the quality of the population, there are three genetic operators to be used in the evolutionary process. They are reproduction, crossover and mutation.

1) Reproduction:

Three steps are required for this operation. The first step is to select the individual from the parent generation using a kind of method. Usually the selection method is based on the probability to allow the better individual to have a better opportunity to be selected. The second step is to evaluate the selected individual. Fitness value will be used in this step. The last step of this operation is to decide whether the selected individual could be duplicated and how many copies the selected individual should be duplicated.

The reproduction operation is to ensure that a stronger individual has a better opportunity to be duplicated and a poor individual has a low probability to be reproduced. Reproduction operator's main function is to give preference to better or stronger individuals, allowing them to pass on their 'genes' to the next generation. In this operation, the goodness of each individual depends on its fitness, and the fitness could be determined by an objective function or by a subjective judgement.

Reproduction operation is a very important operator to make the individuals in the population to get better and stronger generation by generation.

2) *Crossover:*

Crossover operator represents mating between individuals. In this operation, two individuals are chosen from the population randomly. In this step, the crossover probability should be determined in advance to decide how many individuals could be chosen from the parent generation to implement the crossover operation. Then according to crossover operation rules, the parts or positions to be swapped between the two individuals need to be identified. After swapping the two parts selected from the two parent individuals, the two new individuals are then generated.

Crossover operator is used to increase the diversity of the individuals in the population.

3) *Mutation:*

With a very low probability, some of the individuals will be selected from the population to apply the mutation operator. In this operation, part (a') of the individual will be changed to another part (b') according to a rule, and the two parts should meet the specific requirements. After mutation, a new individual is generated.

This operation's main purpose is to improve the diversity of the individuals within a population. It is also an effective way to improve the quality of the population.

An entire genetic programming process can be summarized in the following steps:

(1) The initial population should be created first.

(2) The rules should be defined to achieve the fitness values of the individuals in the population.

(3) Conduct the reproduction operation to create the individuals in the next generation using the fitness values obtained in the second step.

(4) Perform crossover and mutation operations after reproduction operation is applied.

(5) A generation is achieved if the number of the individuals in the new generation is same as the number of the individuals in the previous generation.

(6) Calculate the average fitness value of the new generation and pick up the individual with the largest fitness value in this generation. Check whether the optimal individual has been achieved. If the answer is yes, stop the evolution process, otherwise go to Step (3).

The basic structure of GP is given in Figure 2.3.

2.3 Gienow – A Typical OKP Manufacturing Company

The research is conducted through collaboration with Gienow Windows and Doors (Calgary, Canada), an OKP company with customized products of windows and doors. Product data and customer requirements used in the case studies of this research are collected from Gienow.

```
Standard GP ()
{
create initial population;
perform evaluation of the initial population;
while the optimal individual is not identified
        {
        calculate population fitnesses;
        conduct reproduction operation;
        conduct crossover operation and mutation operation;
        evaluation population;
        }
}
```

Figure 2.3 Basic structure of GP

Gienow Windows and Doors Ltd. was founded with the founder named Bernard Gienow in 1947 at the owner's hometown, Calgary, Alberta, Canada. Since then, Gienow has experienced the fast development period, and has become a middle sized home builder company with around 800 employees, from originally 37 employees. In 2001, Gienow was named the most innovative manufacturing plant in North America. In 2002, Gienow was honoured at the Canadian Information Productivity Awards for its Integrated Manufacturing System.

As a traditional OKP manufacturing company, Gienow manufactures different kinds of windows and doors products according to the requirements of customers. For doors, there are Stanley residential exterior doors, exterior French doors, sliding vinyl patio doors and industrial grade doors, etc. As for windows, Gienow can offer wood windows, clad windows, vinyl windows, and so on. Over the past decades, because of more attention on research on windows and doors and development of windows and doors according to the requirements from customers, Gienow's products have been spread across North America, Japan, European, China, and South Korea through the extensive dealer network.

In the past two decades, a sophisticated computer system has been developed at Gienow to model the designs based on customer needs, to create requirements of materials, machines, and personnel, and to identify the optimal production schedule. The lead-time from a customer order to the product delivery has been reduced to 3 weeks compared with the average of 2 months in this industry.

In recent years, Gienow has been doing research with University of Calgary to further improve the manufacturing line, update the database, and develop OKP products due to the competitive windows and doors market (Xue et al. 2001, Sun and Xue 2001, Wang and Xue 2002).

In this research, based on the windows products in Gienow, we developed a computer-aided design system to identify the optimal design according to the requirements of customers using optimization methodologies and tools.

2.4 Summary

In this chapter, one-of-a-kind production, product design, AND/OR tree modeling, multi-level optimization approach, multi-objective optimization method, and genetic programming have been introduced. This chapter focuses more on the methodologies used in our research. Gienow Windows and Doors Ltd. is briefly presented at the end of this chapter.

CHAPTER 3: OKP PRODUCT MODELING AND EVALUATION

This chapter discusses the issues on modeling and evaluation of OKP product design in terms of customer requirements. In this chapter, AND/OR trees are used to model the variation of OKP product configurations and parameters. Evaluation measures of customer requirements are defined as functions of design configurations and parameters. In the research as presented in this chapter, different design evaluation measures are integrated by using multi-objective optimization approach. The AND/OR tree can be used for identifying the optimal design configuration and its parameters through a computer search in order to maximally satisfy requirements of customers.

3.1 Introduction

OKP (One-of-a-Kind Production), as mentioned in previous chapters, is a manufacturing method or mode that provides products based upon requirements from individual customers while maintaining the quality and efficiency of mass production (Tu 1997, Wortmann 1997). Compared with the traditional mass production mode where costs of production are reduced by eliminating the numbers of product variations, one-of-a-kind production can better satisfy the various requirements from individual customers.

Although the OKP has been considered as a promising approach to meet today's market demands, this approach also faces many challenges due to the large variations of OKP products. The excessive variety also causes problem in design and manufacturing of OKP products (Tseng and Piller 2003). Therefore an effective method for modeling the large variation of OKP products has to be developed. In this research, two types of product variations are considered: configuration variations and parameter variations.

Configuration design is usually modeled as a constraint satisfaction problem (CSP). Aldanondo et al. (2003) discussed the common features of the configuration design problem and tried to solve the product configuration design problem through using the

CSP approach. Xie et al. (2005) developed a generic configuration design approach. Compared with configuration design, parameter design methods have been well established due to the advances of optimization techniques (Arora 1989). In Xue's research (Xue 1997), state-space search and optimization have been employed to solve the configuration design and parameter design problems.

To identify the optimal design based on individual customer requirements, the first step is to model the product family. This model should include the relevant information of the products in the family, such as the different types of components for different configurations of the products, parameters of the components, and so on. In this research, AND/OR tree is employed to model the variation of OKP products in a product family.

Since different products with different configurations and parameters can satisfy the customer requirements, evaluation of these different products based upon customer requirements then needs to be carried out.

In this thesis work, evaluation indices, representing customer satisfaction levels, are used to evaluate the different product designs. In this research, evaluation of product is conducted through the following steps.

Step 1: Model the relations between products configurations with parameters and evaluation measures of customer requirements.

Step 2: Convert the different evaluation measures with different units into comparable evaluation indices of customer satisfaction.

Step 3: Integrate different evaluation indices into an overall evaluation index (overall customer satisfaction).

In this research, evaluation measures of customer requirements are defined as functions of product configurations and parameters. The non-linear relations between the product evaluation measures and the product evaluation indices are identified using the least-square curve-fitting method (Hoffman 1992). The different product evaluation indices are integrated into an overall evaluation index through multi-objective optimization method (Roman et al. 1995).

Since design and manufacture of OKP products are usually conducted by using sophisticated software systems to manipulate various product development activities including acquisition of customer requirements, modeling and identification of design results, planning and control of manufacturing process, and so on (Tseng and Piller 2003), in this thesis work, a prototype system has also been implemented in Microsoft Visual C++ environment. The issues on the implementation of the software system will be discussed in Chapter 5.

3.2 Modeling of OKP Products

In this section, the variations of product configurations and parameters in an OKP product family are discussed first. Requirements and schemes to model the variations of OKP product configurations and parameters are then explained. Subsequently, creations of the individual customized products from the product family model are presented.

3.2.1 Configurations and Parameters of OKP Products

Based on the literature review given in Chapter 2, configuration variations and parameter variations have to be considered in modeling OKP products.

In this research, a configuration is modeled by combining different components with different sub-functions to satisfy customer requirements. For example, the window products at Gienow are primarily classified into categories of clad windows, wood windows, and vinyl windows in terms of the materials. The windows are also classified as casement windows, awning windows, picture windows, and slider windows according to the styles. These different windows represent different configurations of the window products.

Parameters are used to provide detailed information of the components for different product configurations. For example, the dimensions of length and height are two design parameters of a window product.

Parameters include continuous parameters (e.g., length of the window, width of the window), discrete parameters (e.g., 3*mm* thickness and 6 *mm* thickness of glasses), integer parameters (e.g., 1, 2 and 3 layers of the glasses), and Boolean parameters (e.g., with or without grills).

3.2.2 Modeling of OKP Products

Through extensive study on OKP products, requirements to model the OKP products are achieved as follows:

(1) A customized OKP product is a special variation in a general family of OKP products. For instance, a wood casement window of 900 *mm* by 600 *mm* in size with screen, grills and double glazing (two layers of glass) is a customized OKP product in the family of wood casement window. Therefore, the modeling of the generic OKP products and creation of the customized OKP product from the family of the generic OKP products is required.

(2) The variations of OKP products include both variations of product configurations and variations of OKP parameters. For example styles (e.g., casement, awning), materials (e.g., wood, vinyl), screens, grills, etc. are considered as configuration variations of the window products, while the widths, heights, colors, etc. are considered as parameter variations of the window products. Therefore, the modeling of both the configuration variations and the parameter variations is needed.

(3) Compared with the traditional product family design with limited number of variations including configuration variations (e.g., Honda Accord LX, EX, LX V-6, EX V-6) and parameter variations (e.g., horsepower, size, color of the Honda

Accord), the variations of configurations and parameters for OKP products can not be modeled using the exhaustive method. For instance, 48 configurations are required for modeling the window products by only considering styles, materials, screens, and grills, and each configuration can be produced with unlimited number of different sizes. Therefore a sophisticated computer tool is required for modeling the OKP products.

In this research, the different product configurations in a product family are modeled by an AND/OR tree based on the functions and structures of the products. When a product function/structure can be decomposed into a number of sub-functions or sub-sub-functions/structures, these functions/structures are associated with an AND relation. When a product function/structure can be satisfied by alternative functions/structures, these functions/structures are associated with an OR relation. Each function/structure node in the AND/OR tree is further modeled by parameters, including continuous parameters, discrete parameters, integer parameters and Boolean parameters.

Figure 3.1 shows the variations of window products modeled by an AND/OR tree. The variations of configurations are described by the alternative styles and materials of the window products using AND and OR relations. The parameters are associated with the nodes of this AND/OR tree.

In the example given in Figure 3.1, the AND/OR tree is modeled by 10 nodes. These 10 nodes are further described by parameters including width and height of the window, color, direction of window opening, and so on.

3.2.3 Creation of Customized OKP Products

When a family of OKP products is modeled using an AND/OR tree, the individual OKP products can then be created from the AND/OR tree through state-space search (Xue 1997).

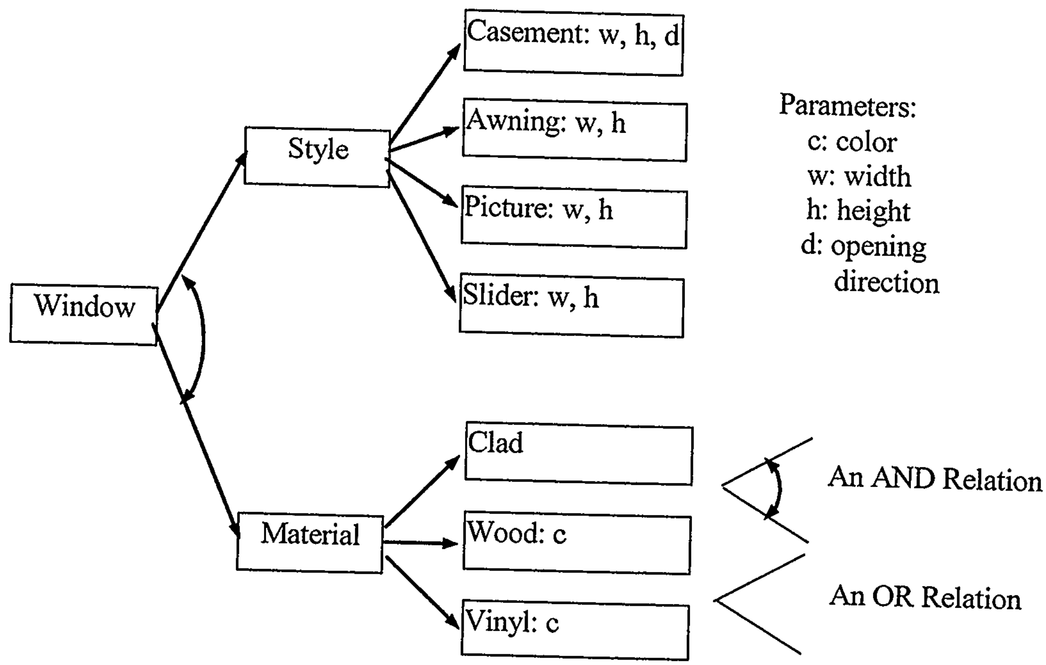


Figure 3.1 An AND/OR tree for modeling variations of OKP products with hierarchical structure

In general, when an AND/OR tree is used for creating feasible individual candidate OKP products through search, the following conditions have to be satisfied during the search process:

(1) The root node has to be selected first.

(2) When a node is selected, if the node's sub-nodes are associated with an AND relation, all these sub-nodes should be selected.

(3) When a node is selected, if the node's sub-nodes are associated with an OR relation, only one of these sub-nodes should be selected.

Figure 3.2 shows some of the 12 feasible product configurations created from the AND/OR tree given in Figure 3.1. Each feasible product configuration is modeled by a tree with only AND relations. Parameters are assigned with values in the customized OKP products.

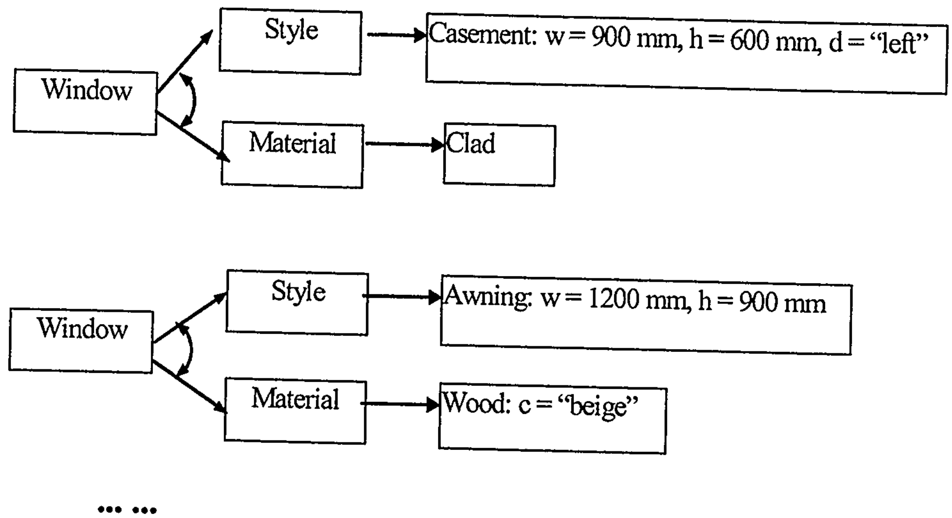


Figure 3.2 Feasible OKP products created from the AND/OR tree

Since a feasible product configuration is described by a collection of nodes and each node is described by a collection of parameters, a product configuration, P_i, can then be described by a set of parameters:

$$P_i = \{X_{i1}, X_{i2} \cdots\cdots, X_{in}\} \tag{3.1}$$

The parameters in Equation (3.1) include continuous, discrete, integer and Boolean parameters.

3.3 Modeling of Customer Requirements and Evaluation of OKP Products Considering Multiple Evaluation Measures

OKP products are designed and manufactured based on the customer requirements. Since many individual products can be created from the same product family, modeling of the customer requirements and evaluation of design candidates based upon the requirements of customers are then needed. This section discusses the issues for modeling customer requirements and evaluation of different OKP design candidates based on the customer requirements.

To identify the optimal product from all feasible candidates based on customer requirements, evaluation of products in terms of customer requirements is needed. In OKP product design, usually many evaluation aspects, such as functional performance, production cost, operation cost, maintenance cost, etc., have to be considered. Some of the evaluation measures may be in conflict. Multi-objective optimization is an effective approach for identifying the optimal design with the best trade-off among various design evaluation measures (Roman et al. 1995).

3.3.1 Modeling of Product Evaluation Measures

Customized OKP products are manufactured based upon requirements from individual customers. Since a customized OKP product is created from the generic family of OKP products with variations in configurations and parameters, evaluation of an OKP product can then be carried out by evaluating the product configuration and its parameters.

Usually customer requirements are modeled by various evaluation measures that are functions of design parameters. For instance, customer requirements of a window product can be described by performance functions and cost functions, such as ventilation area, heat loss rate, product cost, maintenance cost, etc.

In this research, evaluation of a product configuration, P, with n parameters in the *i-th* evaluation aspect is defined by:

$$f_i = f_i\,(X_1, X_2, \ldots\ldots, X_n) \qquad (3.2)$$

In OKP, customer evaluation measures are usually classified into two categories (Xue and Dong 1998): performance measures, P_i, such as power output and efficiency of a power system, and cost measures, C_i, such as product cost and maintenance cost. Different products have different evaluation measures due to their special characteristics. For example, an automobile can be evaluated by the noise level, the weight, the product cost, the maintenance cost, the maximum speed it can reach, and so on.

Even the same evaluation measures are selected by customers for evaluating an OKP product, different customers may focus on different evaluation measures. For instance, some of the customers may pay more attention to the price. Some other customers may focus more on the product performance. The different importance factors of evaluation measures can be modeled as weighting factors of these evaluation measures (Yang et al. 2005).

Equation (3.2) and (3.3) show an example to evaluate a window product in terms of a performance measure, ventilation area, and a cost measure, product cost.

$$\textit{Ventilation-Area } (m^2)\text{: } P_{vent} = 0.75wh \tag{3.2}$$

$$\textit{Product-Cost } (\$)\text{: } C_{product} = (0.2153wh + 0.2540) \times 10^3 \tag{3.3}$$

where w and h are the width and the height of the window product in the unit of meters.

In Equation (3.2) and (3.3), the two conflicting evaluation measures are considered together to evaluate the product. Therefore the trade-off between these two evaluation measures has to be considered. The following two problems should be addressed for evaluating an OKP product considering the two evaluation measures given in Equation (3.2) and (3.3).

- Problem 1: The two evaluation measures are in conflict. When the ventilation area is maximized, the product cost is also increased correspondingly.

- Problem 2: The two evaluation measures are modeled in different units. For the ventilation area, the unit of m^2 is used. For the product cost, the unit of *dollars ($)* is employed. These different evaluation measures with different units cannot be combined directly to evaluate the OKP product.

When a number of evaluation measures are used as objective functions to identify the optimal design, the design problem is usually formulated as a multi-objective optimization problem (Marler and Arora 2004). In this research, a new method has been developed to solve the multi-objective optimization problem by converting the multi-objective optimization problem into a single-objective optimization problem.

3.3.2 Modeling of the Non-linear Relations between Product Evaluation Measures and Customer Satisfaction Indices Using Least-square Curve-fitting Method

Since the different product evaluation measures are usually described in different units, such as kilowatt, percentage and dollars etc., these measures need to be converted into comparable measures for evaluating the product considering all relevant evaluation aspects (Yang et al. 2005).

Because the units of the product evaluation measures are usually different, these measures cannot be simply combined together to evaluate the products. In this research, these different product evaluation measures are converted into comparable customer satisfaction measures, called customer satisfaction indices described by values between 0 and 1, to evaluate the products. The relations between evaluation measures and evaluation indices (i.e., satisfaction levels of customers) are not always linear relations. For example, customers are usually very satisfied with the car when it can break from 60 *km/hour* to stop within 1 *second*. The satisfaction will dramatically decrease if the breaking time changes close to 2 *seconds*. The relation between the breaking time of the car and customer satisfaction is a non-linear relation. Table 3.1 shows the non-linear relation between the car breaking time and the customer satisfaction indices.

In this thesis work, pairs of evaluation measures and their corresponding evaluation indices are selected first. The least-square curve-fitting method (Hoffman 1992) is then used to model the continuous non-linear relation between the product evaluation measures and the customer satisfaction indices.

Table 3.1 Non-linear relations between car breaking time and the customer satisfaction indices

Car breaking time ($T_{breaking}$)	Customer satisfaction index ($I_{breaktime}$)
0.2s	1.00
0.5s	0.95
1.0s	0.85
1.5s	0.50
1.9s	0.10

If the i-th evaluation measure is defined as $f_i(X)$, and its evaluation index is defined as $I_i(X)$, the relation between this evaluation measure and its evaluation index can be described by:

$$I_i(X) = F_i[f_i(X)], \quad i = 1,2,\cdots,m \tag{3.4}$$

The relation between an evaluation measure, $f_i(X)$, and its evaluation index, $I_i(X)$, is usually a non-linear relation. For example, Table 3.2 shows the relation between the ventilation area and its customer satisfaction index. From the table, we can see the customer satisfaction improves with the increase of ventilation area. When the ventilation area is over 1.0 m^2, the customer feels very satisfied with the product, and the corresponding customer satisfaction index reaches to 0.9, which means the customer satisfaction is quite high and cannot be significantly improved when the ventilation area is further increased. Meanwhile, when the ventilation area is less than 0.3 m^2, the customer feels extremely unsatisfied with this window product due to the ventilation problem.

In Table 3.2, the non-linear relation is described by 4 pairs of discrete points. In optimization, however, a continuous function between an evaluation measure and its evaluation index is usually required. In this research, least-square curve-fitting method (Hoffman 1992) is used to identify this continuous function.

Table 3.2 Non-linear relations between ventilation areas and ventilation satisfaction indices

P_{vent}: Ventilation area (m^2)	I_{vent}: Customer satisfaction index
0.3	0.00
0.4	0.35
0.6	0.70
1.0	0.90

The non-linear relations between an evaluation measures, $f_i(X)$, and its evaluation index, $I_i(X)$, is defined by a cubic polynomial in the form of:

$$I_i(X) = a_{0,i} + a_{1,i} \cdot f_i(X) + a_{2,i} \cdot f_i^2(X) + a_{3,i} \cdot f_i^3(X), \quad i = 1,2,\ldots,m \tag{3.5}$$

Where, $a_{0,i}$, $a_{1,i}$, $a_{2,i}$, and $a_{3,i}$ are the four coefficients of the cubic polynomial function. When a number of $f_i(X)$ values and their corresponding $I_i(X)$ values are given, the 4 coefficients of the polynomial function in the Equation (3.5) can be obtained using the least-square curve-fitting method.

Figure 3.3 shows the relation obtained using the least-square curve-fitting method based on the 9 pairs of $f_i(X)$ and $I_i(X)$ data.

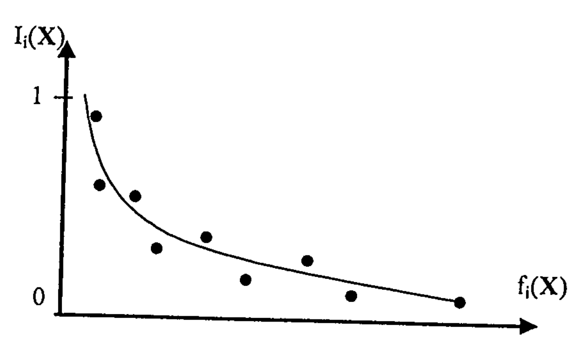


Figure 3.3 Least-square curve-fitting method

For example, when ventilation area (m^2) and production cost ($) are selected to evaluate the product, these two evaluation measures need to be converted into ventilation evaluation index (i.e., ventilation satisfaction index) and production cost evaluation index (i.e., product cost satisfaction index).

According to the data given in Table 3.2, the relation between the ventilation area, P_{vent}, and the ventilation area evaluation index, I_{vent}, is identified as

$$I_{vent} = 0.3209P_{vent}^3 - 1.4994P_{vent}^2 + 2.3318P_{vent} - 0.2486 \quad (3.6)$$

The continuous relation is also plotted in Figure 3.4.

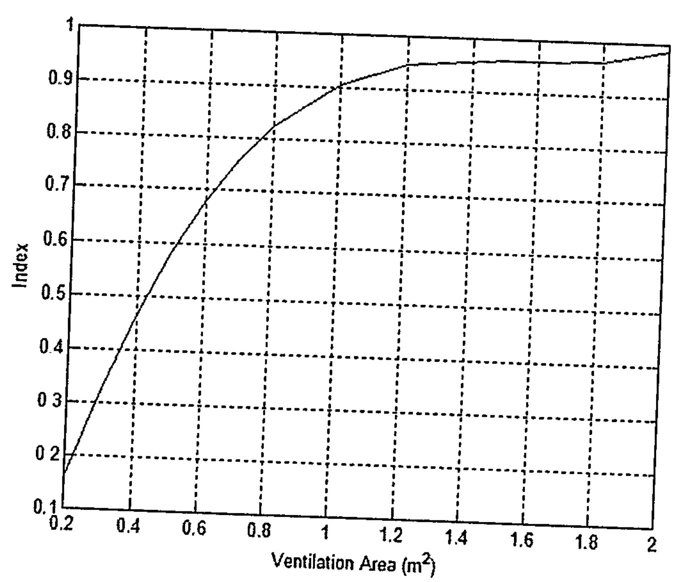


Figure 3.4 Non-linear relations between ventilation areas and ventilation satisfaction indices identified using least-square curve-fitting method

Using the same method, based on the data given in Table 3.3, the non-linear relation between product cost, $C_{product}$, and product cost satisfaction index, $I_{product}$, can be achieved as:

Table 3.3 Non-linear relations between product costs and customer satisfaction indices

$C_{product}$: **Product cost** *($)*	$I_{product}$: **Customer satisfaction index**
250	1.00
750	0.90
1,500	0.70
2,000	0.50
3,000	0.25

$$I_{product} = 0.043C_{product}^3 - 0.2133C_{product}^2 - 0.006C_{product} + 1.0213 \qquad (3.7)$$

Figure 3.5 shows the continuous relation between product cost, $C_{product}$, and product cost satisfaction index, $I_{product}$. When the product cost decreases, customer satisfaction will increase.

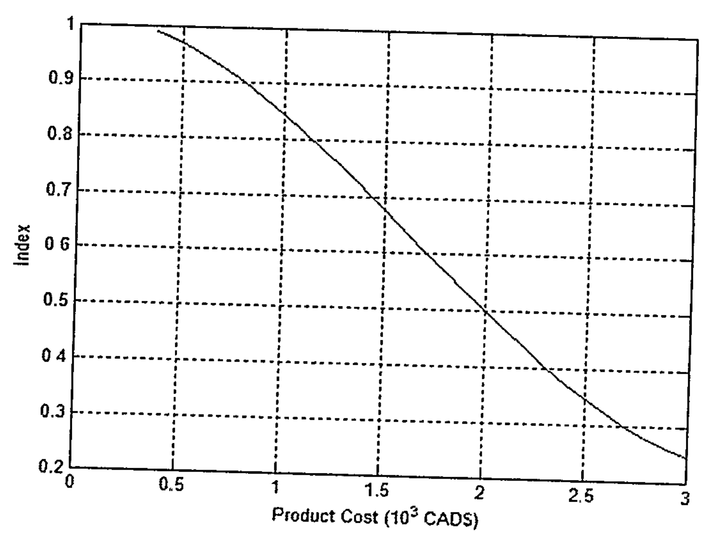


Figure 3.5 Non-linear relations between product costs and product cost satisfaction indices identified using least-square curve-fitting method

3.3.3 Identification of Weighting Factors for Different Evaluation Indices Using the Pair-wise Comparison Method

When multiple evaluation measures are considered, these measures need to be first converted into evaluation indices. The tradeoff among these evaluation indices is then considered to evaluate the product considering all the selected evaluation aspects.

Some researchers have strived to develop design metrics for tradeoff analysis in customized products identification (Jiao and Tseng 2004). Martin and Ishii (1996, 1997) developed quantitative tools to determine customer preference. Gongzalez-Zugasti et al. (2001) proposed a quantitative measure to evaluate product families considering the factors of different evaluation measures. Conner et al. (1999) applied robust design principles to address product family tradeoffs using the commonality and performance indices developed by Simpson (1998). All the above methods are complex, and not easy to be implemented. In this research, Satty's pair-wise comparison method is employed to obtain the importance values of the different product performance and costs.

In this research, the overall product evaluation is conducted based on the all aspects of the product evaluation measures. Because the product evaluation measures have been converted into customer satisfaction indices using the least-square curve-fitting method, the values of customer satisfaction can be associated together to evaluate the product according the customer requirements by:

$$I(X) = \frac{W_1 \cdot I_1(X) + W_2 \cdot I_2(X) + \cdots + W_m \cdot I_m(X)}{W_1 + W_2 + \cdots + W_m} \tag{3.8}$$

where W_1, W_2, ..., W_m are m weighting factors for the m product evaluation indices according to the customer requirements, and the $I(X)$ is called the overall customer satisfaction index. Weighting factors represent the importance measures of these evaluation indices (Yang et al. 2005).

3.3.3.1 Pair-wise Comparison Method

The weighting factors are usually assigned directly by the customers or the product salespersons. When a large number of evaluation measures are considered, since most of these weighting factors are achieved by comparing with a reference weighting factor, inconsistency among weighting factors of these evaluation measures sometimes can be identified. In this research, the pair-wise comparison method (Satty 1980) is employed to identify the weighting factors by comparing each of the evaluation measures with all other evaluation measures.

Satty's pare-wise comparison method was developed in their research on analytic hierarchy process (AHP). In this method, all pairs of evaluation aspects should be compared in pair-wise to estimate their relative importance. Every time, only two items are picked up from all the items to determine which one is more important.

In this research, all the product evaluation measures need to be compared with each other. The importance scale is shown in Table 3.4 according to Satty's pair-wise comparison method.

If there are m product evaluation measures, the values of the weighting factors can be obtained through pair-wise comparison method in the following steps.

First, the relative importance between two evaluation measures should be obtained according to Table 3.4. For instance, if the *i-th* product evaluation measure is selected to compare with the *j-th* product evaluation measure, the relative importance can be calculated by:

$$a_{ij} = {}^{w_i}\!/_{w_j} \qquad (3.9)$$

where w_i and w_j represent the *i-th* and the *j-th* weighting factors of customer requirements, respectively.

Table 3.4 Importance scale according to Satty's comparison method

No.	Relative importance between two items (A/B)	The ratio of A to B
1	Overwhelmingly more important	9
2	Between No. 1 and No. 3	8
3	Very strongly more important	7
4	Between No. 3 and No. 5	6
5	Strongly more important	5
6	Between No. 5 and No. 7	4
7	Moderately more important	3
8	Between No. 7 and No. 9	2
9	Equally important	1

Then, the equation to calculate the weighting factors is achieved using the available pair-wise ratios. When all the m evaluation measures are compared in pair wise, an $m \times m$ matrix will be obtained. The pair-wise ratios satisfy:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \cdots \\ w_m \end{bmatrix} = \lambda_{\max} \begin{bmatrix} w_1 \\ w_2 \\ \cdots \\ w_m \end{bmatrix} \tag{3.10}$$

where $w_1, w_2, \ldots, w_m$ are the weighting factors for Equation (3.8), and λ_{max} is the largest one of the eigenvalues of the matrix. Because every design evaluation measure is equally important as itself, and the upper triangle of the matrix is reciprocal to the lower triangle of the matrix, only $m(m-1)/2$ times of the comparisons are required. Equation (3.10) can be simplified as:

$$AW=\lambda W \tag{3.11}$$

or

$$(A\text{-}\lambda I)\boldsymbol{W}=\boldsymbol{0} \tag{3.12}$$

where I is the identity matrix, and λ is the eigenvalue of A. The $\boldsymbol{W}$ is the eigen-vector for the maximum eigenvalue λ_{max} ($\lambda_{max} \geqslant \lambda$).

At last, the values of the weighting factors should be checked. Because the matrix of A in Equation (3.11) is generated through human judgment, and the human judge is not consistent to some degree, the inconsistency of the judgement needs to be considered. The consistency index CI, introduced by Satty (1980), is the measure to evaluate the deviation from consistency of pair-wise ratios. CI is obtained using

$$CI = (\lambda_{\max} - m)/(m-1) \tag{3.13}$$

When values of the ratios are generated randomly, the consistency index is represented by RI. The average RI values for different orders of matrices are summarized in Table 3.5.

Table 3.5 Average consistency indices for random reciprocal matrices with different orders

m	2	3	4	5	6	7	8	9	…
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	…

The ratio of CI to RI defined by

$$CR = CI / RI \tag{3.14}$$

for the same order matrices is called the consistency ratio (CR). For any pair-wise ratio matrix with the consistency ratio less than 0.10 is looked as an adequate ratio matrix. The weighting factors of indices are obtained by calculating the eigen-vector corresponding to the maximum eigenvalue λ_{max} in Equation (3.11).

Usually the weighting factors for different design evaluation measures are obtained using the pair-wise comparison method. In this research, Matlab has been used for achieving the maximum eigenvalue and its eigen-vector.

3.3.3.2 *An Example for Identifying the Weighting Factors Using the Pair-wise Comparison Method*

An example is given to show how the weighting factors are achieved using the pair-wise comparison method. The six evaluation measures in this example are described in Table 3.6.

Table 3.6 Product evaluation measures

Evaluation measure		**Unit**	**Symbol**
Performance 1	Ventilation area	Square meters	P_{vent}
Performance 2	Viewing area	Square meters	P_{view}
Performance 3	Rain risk area	Square meters	P_{rain}
Performance 4	Heat loss	Watt per degree	P_{heat}
Cost 1	Product cost	Canadian dollars	C_p
Cost 2	Maintenance cost	Canadian dollars	C_m

The pair-wise comparison ratios for designing a particular product were obtained from the experience of design engineers. Table 3.7 shows these pair-wise comparison ratios among the selected six evaluation measures. These ratios are used to form the following equation based on Equation (3.10).

$$\begin{bmatrix} 1 & 7/9 & 7/3 & 7/6 & 3/2 & 5/3 \\ 9/7 & 1 & 9/4 & 8/7 & 5/4 & 7/4 \\ 3/7 & 4/9 & 1 & 3/5 & 2/3 & 3/4 \\ 6/7 & 7/8 & 5/3 & 1 & 2/3 & 6/9 \\ 2/3 & 4/5 & 3/2 & 3/2 & 1 & 3/2 \\ 3/5 & 4/7 & 4/3 & 9/6 & 2/3 & 1 \end{bmatrix} \begin{bmatrix} W_{vent} \\ W_{view} \\ W_{rain} \\ W_{heat} \\ W_p \\ W_m \end{bmatrix} = \lambda_{max} \begin{bmatrix} W_{vent} \\ W_{view} \\ W_{rain} \\ W_{heat} \\ W_p \\ W_m \end{bmatrix} \quad (3.15)$$

Table 3.7 Pair-wise comparison ratios among the six evaluation measures

	P_{vent}	P_{view}	P_{rain}	P_{heat}	C_p	C_m
P_{vent}	1	7/9	7/3	7/6	3/2	5/3
P_{view}	9/7	1	9/4	8/7	5/4	7/4
P_{rain}	3/7	4/9	1	3/5	2/3	3/4
P_{heat}	6/7	7/8	5/3	1	2/3	6/9
C_p	2/3	4/5	3/2	3/2	1	3/2
C_m	3/5	4/7	4/3	9/6	2/3	1

Using the functions in Matlab software package, we can get the maximum eigen-value of the matrix and its eigen-vector representing the weighting factors of the design evaluation measures.

In this example, the maximum eigen-value, λ_{max}, is obtained as 6.0965. The weighting factors are achieved by calculating the eigen-vector corresponding to the maximum eigen-value. These weighting factors for the six evaluation measures (i.e., ventilation area, viewing area, rain risk area, heat loss, product cost and maintenance cost) are obtained as:

$W_{vent} = 0.5024$

$W_{view} = 0.5280$

$W_{rain} = 0.2343$

$W_{heat} = 0.3509$

$W_p = 0.4203$

$W_m = 0.3379$

Using Equation (3.8), the overall customer satisfaction index of the selected product is obtained as:

$$I(X) = \frac{W_{vent}I_{vent}(X) + W_{view}I_{view}(X) + W_{rain}I_{rain}(X) + W_{heat}I_{heat}(X) + W_pI_p(X) + W_mI_m(X)}{W_{vent} + W_{view} + W_{rain} + W_{heat} + W_p + W_m} \tag{3.16}$$

3.3.4 Summary

Based on the above discussions in this chapter, the procedure to reach the overall customer satisfaction evaluation measure is described in Figure 3.6.

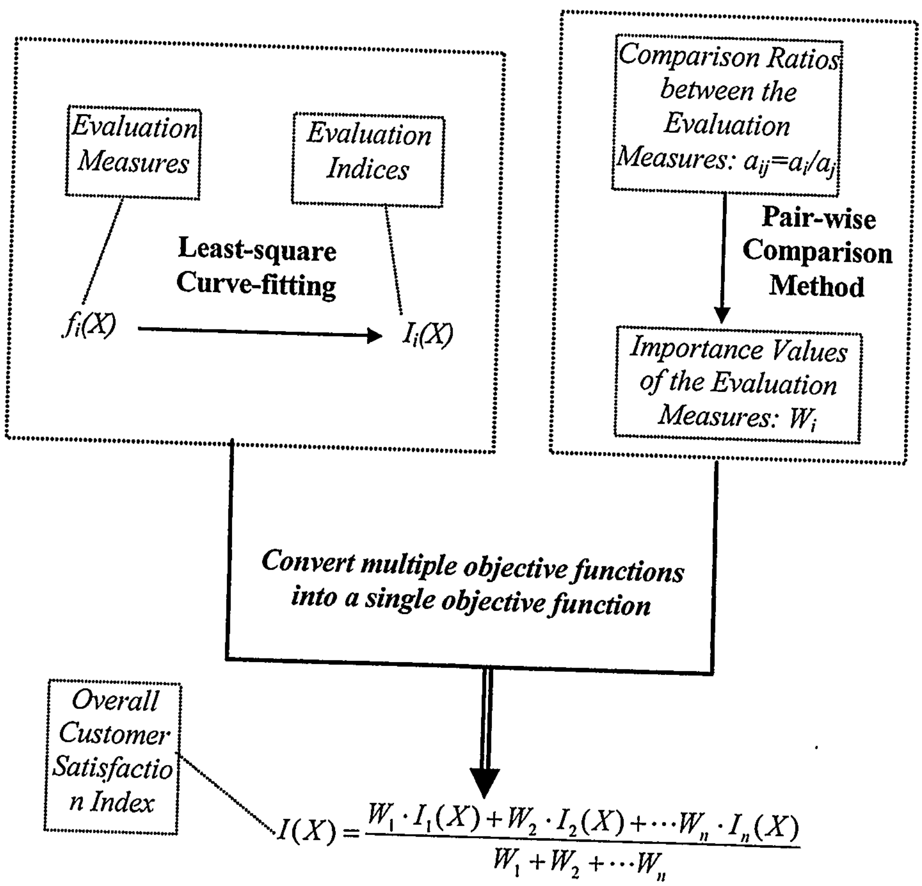


Figure 3.6 The procedure to obtain the overall customer satisfaction index

In this thesis work, the different design evaluation measures are integrated by using multi-objective optimization method to evaluate the product. The least-square curve-fitting method and pair-wise comparison technique are employed to convert the multiple evaluation functions with different units into a single evaluation function. In this research, the overall customer satisfaction index is used to evaluate the design.

3.4 Summary of This Chapter

In this chapter, first of all, modeling of OKP products by using AND/OR trees is discussed. Then integration of different evaluation measures is explained through using the multi-objective optimization approach to evaluate the product design candidates. The evaluation of design candidates serves as the basis for identifying the optimal product design from all the feasible design candidates using optimization that will be introduced in the next chapter.

CHAPTER 4: IDENTIFICATION OF THE OPTIMAL OKP PRODUCT

In this chapter, a multi-level and multi-objective optimization approach is introduced to identify the optimal OKP product design from an AND/OR tree of product family.

4.1 A Multi-level and Multi-objective Optimization Approach

Since the different configurations and the parameters of an OKP product can be evaluated by the overall customer satisfaction index, the optimal product configuration and its parameters can be derived through solving the optimization problem which uses the maximum overall customer satisfaction index as the objective function subject to the constraints, such as cost, technical requirements, etc. In this thesis, the customer satisfaction indices in fact represent objective functions in multi-objective optimization. The optimization is also conducted at two different levels, i.e., configuration level and parameter level.

Suppose a feasible configuration is defined by its parameters:

$$P_i = \{X_{i1}, X_{i2}, \cdots, X_{in_i}\} \tag{4.1}$$

The optimal parameter values for one product configuration can be obtained by solving the following optimization problem:

$$\underset{w.r.t.\, X_{i1}, X_{i2}, \cdots, X_{in_i}}{Max} \; I_i(X_{i1}, X_{i2}, \cdots, X_{in_i}) \tag{4.2}$$

subject to:

$$X_{ijL} \le X_{ij} < X_{ijU}, \; j = 1,2,\cdots,n_i$$

$$h_{ij}(X_{i1}, X_{i2}, \cdots, X_{in_i}) = 0, \; j = 1,2,\cdots,k_i$$

$$g_{ij}(X_{i1}, X_{i2}, \cdots, X_{in_i}) \le 0, \; j = k_i+1, k_i+2, \cdots, m_i$$

The optimal objective function evaluation measure for configuration P_i is described as $I_i(P_i^*)$. The optimal configuration is identified from all feasible configurations by using:

$$\underset{w.r.t.\,P_i^*}{Max}\; I_i(P_i^*) \tag{4.3}$$

where P_i^* is iterated among the feasible configurations with the optimal parameter values. Since the optimization is conducted at two different levels, it is obviously a multi-level optimization problem (Xue 1997). In this thesis work, the genetic programming (Koza 1992) and constrained optimization (Arora 1998) are employed for solving the optimization problems respectively on the configuration and parameter levels.

The configuration optimization is used to identify the components of the optimal OKP product from an AND/OR tree. The parameter optimization is employed to achieve the design parameters (e.g., dimensions) of the selected design configuration. For instance, if a diesel engine is to be designed, first of all the components of the diesel engine, such as cylinders, pistons, crank shafts, cylinder heads, base of the engine, etc., should be selected. Then the detailed parameters, such as the diameter of the cylinder, the length of the piston, the number of the piston rings, the cubage of the combustion chamber, etc., are determined according to the requirements of customers.

In this thesis work, the multi-level optimization technique is used to identify the optimal design of a customized window which belongs to a window product family. The window product family is modeled by an AND/OR tree. At the configuration optimization level, material, style and features (e.g., grills, glazing, screen, and glass type) of the window are decided. At the parameter optimization level, to each of the feasible product configurations, the length, the width and other dimensions of the window are determined.

In this thesis work, two types of evaluation measures are considered: performance measures and cost measures. These measures with different units are converted into comparable customer satisfaction indices by using the method as introduced in Chapter 3. These evaluation indices, which represent optimization objectives, are integrated by assigning weighting factors to these evaluation indices to form an overall customer satisfaction index function. Hence the multi-objective optimization problem is converted into the single objective optimization problem to maximize the value of the overall customer satisfaction index function. By doing this, it simplifies the problem solving efforts since the single objective optimization problem can be easily solved by using constrained based linear or non-linear mathematic programming or computing numerical methods. From above discussion, it is concluded that the optimal product design problem in this research should be solved through using a multi-level and multi-objective optimization method.

The following sections of this chapter introduce the detailed methods to solve this product design optimization problem. To validate the advantages of the genetic programming method for solving the optimization problem at the configuration level, the exhaustive method is first presented in Section 4.2 to identify the optimal product configuration as a comparison study.

4.2 Identification of the Optimal Product Configuration by Using the Exhaustive Method

Usually two methods can be employed for identifying the optimal product configuration from an AND/OR tree: exhaustive method and genetic programming (Zhang and Xue 2001).

The exhaustive method is a technique that the ancient Greek mathematicians used to solve problems through enumerating all the possibilities. As one of most traditional methods, exhaustive method needs to generate all the feasible choices, and then evaluate all the choices to select the best one among these choices. The exhaustive method can guarantee obtaining the best solution if there is sufficient time on searching and evaluating all the possible solutions.

Exhaustive method provides excellent quality of search results even if it is conceptually simple. Normally this method takes much longer time compared with other methods to solve the same size of problems. In product design optimization, exhaustive method is sometime employed to identify the optimal design from all possible design candidates. When the number of the OKP product candidates obtained from a product family is small, the exhaustive method should be selected for generating all the feasible candidates and identifying the optimal one.

In this thesis research, a family of OKP products is modeled by an AND/OR tree. The exhaustive method to identify the optimal product from the AND/OR tree is formulated in the following 5 steps.

Step (1) Give every node in the AND/OR tree a different name (e.g., A, B, C).

Step (2) Initiate an empty node list. Each node list represents a product configuration.

Step (3) Add the root node of the AND/OR tree as the first node in the node list.

Step (4) Select a node in a node list. If this node has sub-nodes with an AND relation in the AND/OR tree, all these sub-nodes should be added in the node list. If this selected node has sub-nodes with an OR relation in the AND/OR tree, the original node list should be duplicated, and each of the sub-nodes in the AND/OR tree is added to one of the duplicated node lists.

Step (5) Check whether all the nodes in the node lists have been expanded. If there is no unexpanded node in the node lists, all the node lists are then considered as different configurations of the products. Otherwise, go to Step (4).

Figure 4.1 shows an AND/OR tree to be used for creating all the feasible configurations using the exhaustive method. In this AND/OR tree for modeling a family of products, the 10 nodes are labeled with alphabets of a, b, c,..., n. To create the feasible product configurations, all of the nodes should be expanded starting from the root node a. Figure

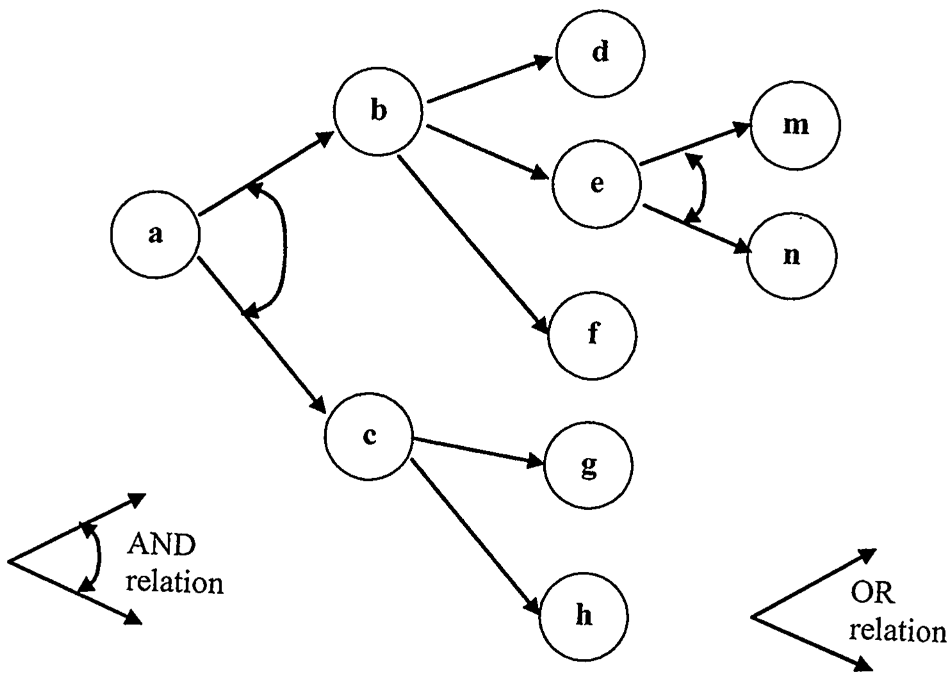


Figure 4.1 An AND/OR tree for modeling a product family

4.2 demonstrates the steps to create all the feasible configurations from the AND/OR tree through using the exhaustive method.

After all the nodes in the AND/OR tree are expanded, a total number of 6 design configurations are generated using the exhaustive method. The 6 configurations are shown in Figure 4.3. Each of the configurations is described by a collection of nodes where the parameters are used to further model the nodes.

After the configurations are achieved through exhaustive method, parameter optimization is conducted to obtain the optimal parameter values for different configurations. The optimal design configuration and its optimal parameters are then identified.

In the example given in Figure 4.1, since the number of the variations in the product family is not large, it is possible to use the exhaustive method to reach the optimal product design. However when the number of the configurations is large, exhaustive method is not effective for identifying the optimal design configuration any more. In this

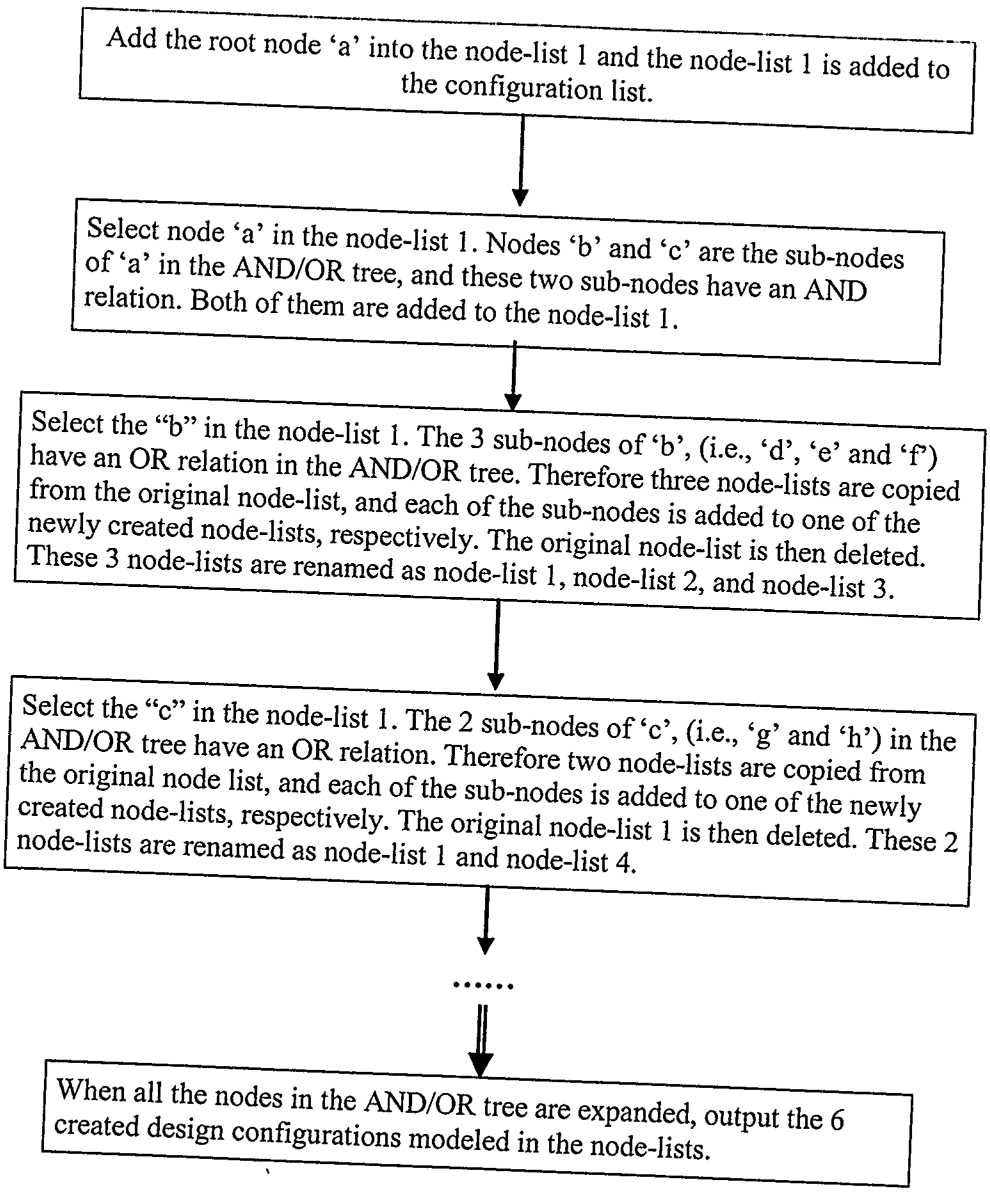


Figure 4.2 The procedure for creating design configurations using the exhaustive method

research, because the OKP product family has a large number of variations, exhaustive method cannot work effectively to identify the optimal OKP product design from the product family. A new effective configuration optimization method, therefore, needs to be developed.

No. 1. a-b-c-d-g
No. 2. a-b-c-e-g-m-n
No. 3. a-b-c-f-g
No. 4. a-b-c-d-h
No. 5. a-b-c-e-h-m-n
No. 6. a-b-c-f-h

Figure 4.3 Six configurations generated through the exhaustive method

4.3 Identification of the Optimal OKP Product Configuration by Using Genetic Programming

As aforementioned, the exhaustive method is usually used for identifying the optimal result from a small number of candidates. However if the number of the product candidates from a product family is large, it will take a long time to generate all the configurations and to identify the optimal product design from all the product candidates using the exhaustive method. In this section of the thesis, the genetic programming is used to identify the optimal product configuration. Comparing with the exhaustive method, it is more efficient since it only selects partial feasible product configurations to formulate a searching pool from a big OKP product family.

The genetic programming is developed from genetic algorithm (Koza 1992). By using the genetic algorithm, a solution is modeled with a fixed-length binary string. Compared with genetic algorithm, usually the solution in genetic programming is described by a data structure, such as a hierarchically structured tree. In the process of evolution, elements and length of the solutions are changed dynamically (Zhang and Xue 2001). Although genetic programming and genetic algorithm are different in modeling problem solutions, they share the same principles of evolution through natural selections.

In this research, to identify the optimal product design from an OKP product family through using the genetic programming, the following three key issues need to be considered:

(1) The first issue is to determine the coding scheme of the solutions properly. In this research, each of the nodes in an AND/OR tree is associated with a unique name. A design configuration, represented by a solution in genetic programming, is created from the AND/OR tree. Each design configuration is modeled by a tree with only AND relations.

(2) The second issue is to select a fitness function. The fitness function is used to evaluate each of the solutions to the optimization problem. In this thesis, the overall customer satisfaction index is selected as the fitness function for evaluating each of the product configurations created from the product family. Details of fitness modeling will be discussed in Section 4.3.1.

(3) The third issue is to model the three genetic operations: reproduction, crossover and mutation. These three operations are employed to generate the next population from the current population. Details of the three genetic operations will be discussed in Section 4.3.2.

4.3.1 Fitness and Fitness Function

Fitness values play important roles in selection of the individuals in a generation for applying the three genetic operations. Fitness function is the objective function in the optimization using genetic programming. For example, only those configurations with good fitness values have chances to be reproduced.

In this research, the overall customer satisfaction index is selected as the fitness to evaluate the product configurations. The corresponding fitness function to obtain the fitness values is generated in terms of product evaluation measures. The products with larger fitness values can better satisfy the requirements of customers.

The overall customer satisfaction index is calculated by using different sub-customer satisfaction indices in different evaluation aspects including performance and costs. The fitness function of the overall customer satisfaction is obtained through the multi-objective optimization approach as introduced in Chapter 3. As aforementioned, pair-wise comparison method and least-square curve-fitting technique are employed in this thesis work to achieve the fitness function. Equation (4.4) shows the final fitness function employed for identifying the optimal OKP product design.

$$I(X) = \frac{\sum_{i=1}^{m} W_i \cdot I_i(X)}{\sum_{i=1}^{m} W_i} \tag{4.4}$$

where $I(X)$ is the overall customer satisfaction index function, W_i is the weighting factor, and $I_i(X)$ is the sub-customer satisfaction index.

4.3.2 General Process of Genetic Programming

In this thesis work, genetic programming is employed to identify the optimal design configuration from an AND/OR tree. The genetic programming is carried out in the following six steps.

(1) Create the initial generation with n individuals. The number of individuals, n, in a generation is pre-selected by the user. Each individual represents a feasible product configuration that is created randomly from the product family which is represented by a tree with only AND relations.

(2) Obtain the overall customer satisfaction index of each individual in the current generation. Each overall customer satisfaction index is used as the fitness of the corresponding individual.

(3) Create a new generation from the current generation by repeating the following sub-steps (i.e., three genetic operations) until the number of the individuals in the new generation reaches n.

(a) Reproduction

Select two individuals in the current generation as the parent individuals according to their fitness values using the roulette wheel selection method which makes the individuals with larger fitness values have more chances to be selected.

(b) Crossover

After reproduction, the crossover probability needs to be calculated. When crossover operation is required, swap the crossover parts from the two selected parent individuals to form two new offspring (children) individuals. If no crossover operation needs to be performed, the two offspring individuals are the exact copies of the two parent individuals.

(c) Mutation

Calculate the mutation probability for each of the two offspring individuals. When the mutation operation is required and the parent individual can meet the requirements for mutation, then mutation operation is implemented to generate a new offspring (children) individual.

(4) Select the newly created generation as the current generation to continue the evolution process.

(5) If the average fitness of a generation cannot be significantly further improved in the last m generations (i.e., the improvement is less than a pre-defined small number ε), or the pre-defined maximum generation g_{max} has been reached, the

evolution process should be stopped and the best individual in the current generation is selected as the optimal product configuration.

(6) Go to Step (2).

In the following sections, the three operations of genetic programming employed in this thesis are introduced in details.

4.3.3 Reproduction

Reproduction is implemented based on the fitness value of each of the solutions to the optimization problem. Reproduction embodies the principle of "survival of the fittest" (Srinivas and Patnaik 1994). Usually, the individuals with larger fitness values have better chances to be selected for reproduction. The individuals with relative small fitness values are eliminated. The reproduction operation makes the individuals in the next generation have better fitness measures.

In the genetic programming used in this research, two parent individuals from the current generation are selected for reproduction of the individuals in the next generation. A parent individual is selected based on its fitness using the roulette wheel selection method. In this method, the size of the section in the roulette wheel is proportional to the value of the fitness function of every individual, which means the greater the value is, the larger the section is. When a marble is thrown in the roulette wheel, the individual where the marble stops is selected. Clearly, the individuals with large fitness values will be selected more times.

The roulette wheel selection method is formulated in the following algorithm:

(a) Calculate the sum, S, of the fitness values, f_i, for all individuals in the population.

(b) Generate a random number, r, from the interval $(0, S)$.

(c) Go through the individuals in population and obtain the sums of the fitness values from the first individual to the i-th individual. When the sums satisfy the condition:

$$\sum_{j=1}^{i-1} f_j < r < \sum_{j=1}^{i} f_j \tag{4.5}$$

The i-*th* individual is then selected for reproduction.

Selection of parent individuals is continued until the number of individuals in the next generation reaches the number of population.

Using the roulette wheel selection method to choose the parent individuals from the current generation for reproduction, the reproduced individuals have apparently larger average fitness value compared with the average fitness value of the individuals in the previous generation. Therefore, reproduction is an important factor in leading the next generation to have better quality of optimization solutions.

In this thesis work, the overall customer satisfaction index is used as the fitness function to evaluate the product individuals. Using the roulette wheel method, the individual products selected from the current generation usually provide higher customer satisfaction measures compared with other individuals which are not selected for reproduction.

Table 4.1 shows 6 individuals in the current generation. These individuals have different overall customer satisfaction index values (fitness values). Using the roulette wheel method, the individuals with larger customer satisfaction index values have more chances to be selected for reproduction. In Table 4.1, the fitness values of individual 'ID_x' is 0.865, much larger than other individuals. So this individual is selected twice for producing 2 copies through the reproduction operation by using roulette wheel method. Meanwhile individual 'ID_y' is not selected for reproduction in the next generation since the fitness value (i.e. 0.135) of this individual is the smallest among the individuals in the current generation.

Table 4.1 The selections of individuals for reproduction

Individuals	Customer satisfaction index	Fitness values	Copies
ID_v	0.555	0.555	1
ID_w	0.678	0.678	1
ID_x	0.865	0.865	2
ID_y	0.135	0.135	0
ID_z	0.758	0.758	1
ID_m	0.655	0.655	1
Average:	**0.607**	**0.607**	**Total: 6**

Table 4.2 shows the 6 individuals in the next generation after the reproduction operation is implemented. Comparing the data in Table 4.1 with the data in Table 4.2, we can find

Table 4.2 Next generation after reproduction

Individuals	Individuals reproduced from current generation	Customer satisfaction indices	Fitness values	Number
ID_v'	ID_v	0.555	0.555	1
ID_w'	ID_w	0.678	0.678	1
ID_x1'	ID_x	0.865	0.865	1
ID_x2'	ID_x	0.865	0.865	1
ID_z'	ID_z	0.758	0.758	1
ID_m'	ID_m	0.655	0.655	1
Average:		**0.729**	**0.729**	**Total: 6**

that the average fitness measures in the next generation after reproduction has been improved from 0.607 to 0.729.

After the implementation of the reproduction operation, crossover and mutation operations are considered for the newly created individuals.

4.3.4 Crossover

Crossover operation is applied to the individuals created by reproduction. Crossover operation increases the diversity of the population by producing the new offspring by exchanging some of the parts of the two selected individuals.

In this thesis research, since each individual is described by an AND/OR tree, the crossover is conducted by selecting a crossover position randomly for each of the two parent individuals and swapping the two sub-trees with the selected positions as the root nodes of the sub-trees.

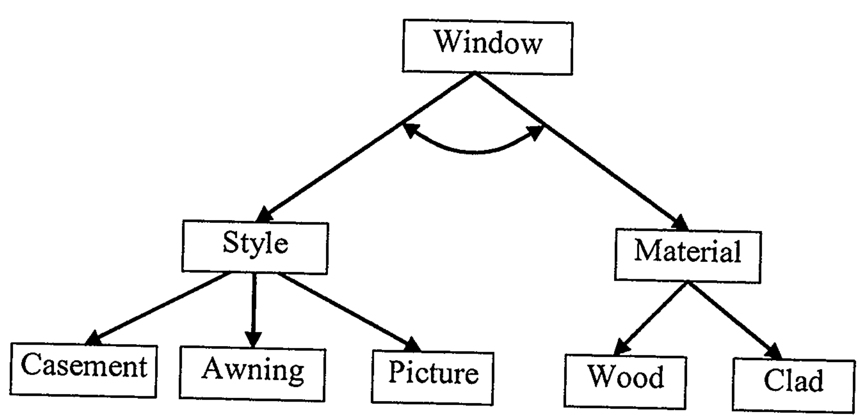


Figure 4.4 The product AND/OR tree

Figure 4.4 shows the AND/OR tree of a window product family. Figure 4.5 gives an example on how crossover operation between the two selected individuals is implemented. The crossover position should satisfy the following conditions:

- The node at the selected location should not be a root node in the product AND/OR tree.

- The two nodes at the selected two locations of the parent individuals for crossover should have an OR relation in the product AND/OR tree.

In Figure 4.5, the crossover operation is implemented between individual *A* and individual *B*. Sub-node 'Clad' in individual *A* has an OR relation with sub-node 'Wood' in individual *B*. Because these two individuals satisfy the conditions of crossover, sub-node 'Clad' in *A* is exchanged with sub-node 'Wood' in *B*. Two new child individuals, *A'* and *B'*, are generated using the crossover operation.

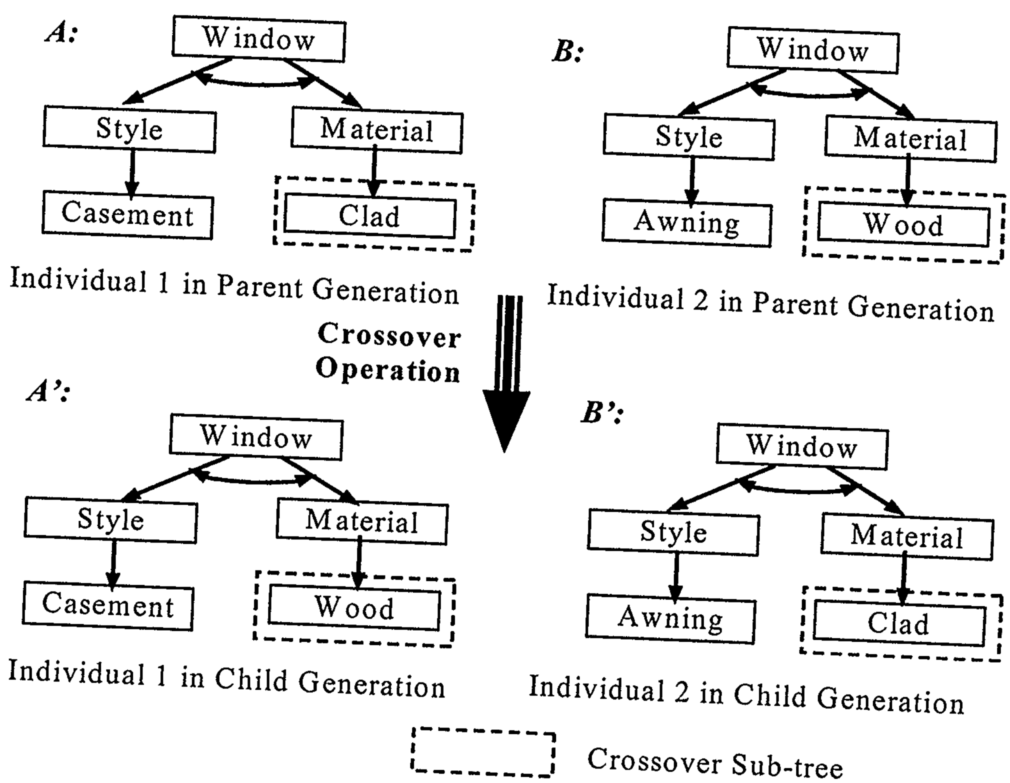


Figure 4.5 Crossover operation

The crossover operation should be conducted with small probability to avoid significant random changes of individuals in the next generation. Usually a threshold crossover probability, $p_{cs}^{(i)}$, is pre-defined. When a created crossover random number, p_{cs} (which is called crossover probability or crossover rate), is greater than the pre-defined number, $p_{cs}^{(i)}$, the crossover operation is then conducted.

To improve the efficiency of genetic programming for achieving the final optimal result, an adaptive method to obtain the crossover probability, p_{cs}, developed by Srinivas and Patnaik (1994) is employed in this thesis research. In this method, crossover probability, p_{cs}, is calculated by the following equation:

$$p_{cs} = \begin{cases} (f_{\max} - f_{bigger})/(f_{\max} - f_{ave}), f_{bigger} \geq f_{ave} \\ 1, f_{bigger} < f_{ave} \end{cases} \tag{4.6}$$

where f_{max} is the maximum fitness value in the population, f_{bigger} is the fitness of one of the two selected parent individuals with larger fitness value, and f_{ave} is the average fitness value for all the individuals in the population.

When each node in the individual is associated with a positive integer (i.e., the first node in the product node list is given '1' as its positive integer), the position of crossover is identified by:

$$L_{cs} = \text{int}[(n-1)P_{cs} + 1] \tag{4.7}$$

where n is the number of nodes in the individual, and P_{cs} is random number between 0 and 1. The function int[] converts a real number to its closest integer.

In this research, crossover position should meet the crossover conditions. If the location, L_{cs}, of the crossover operation cannot meet the conditions, the location is moved one step forward or backward to a new location. The moving direction is determined randomly. If the node at the new location still does not satisfy the crossover condition, the location is continuously moved in the determined direction until a location that satisfies these conditions is found. As long as the location can satisfy the crossover conditions, the crossover operation is then implemented. If the location has reached the top (or bottom) node, the location is changed to the bottom (or the top) of the list to continue this process.

For each of the two parent individuals, once the location of crossover is identified, the sub-tree with the selected position as the "root" node should be replaced by the other sub-tree with the corresponding position as the "root" node from the other parent individual. The two children individuals, which are different from the two parent individuals, are then generated.

Although crossover operation can generate the individuals with smaller fitness values, these individuals have fewer chances to be selected for reproduction in the next generation. When individuals with better fitness measures are created using crossover operation, these individuals are used to lead to the optimal solution.

4.3.5 Mutation

Mutation operation is then selected to apply to the individuals created by crossover operation. The mutation operation is only applied to a single individual. The probability of mutation is usually selected with a smaller number.

In this research, because the product is defined by a tree, mutation operation is implemented through changing the structure of the individual's tree. When an individual is selected for mutation, the mutation position in the individual is first selected randomly. Then the sub-tree with the selected mutation node as the root node is removed from the individual. Another position in the product family AND/OR tree, that has an OR relation with the previously selected mutation node, is then identified as the root node to create a new sub-tree by replacing the removed sub-tree.

The mutation operation should be conducted with small probability to avoid significant random changes of individuals in the next generation. Usually, a threshold mutation probability $p_{mt}^{(t)}$ is pre-defined. When a created mutation random number, p_{mt} (called mutation probability or mutation rate), is greater than the $p_{mt}^{(t)}$, the mutation operation is then conducted.

In this research, the adaptive mutation method developed by Srinvas and Patnaik (1994) is employed to obtain the mutation probability, p_{mt}, for improving the computation efficiency. The mutation probability, p_{mt}, is calculated by:

$$p_{mt} = \begin{cases} 0.5(f_{\max} - f)/(f_{\max} - f_{ave}), f \geq f_{ave} \\ 0.5, f < f_{ave} \end{cases} \tag{4.8}$$

where $f_{\max}$ is the maximum fitness value in the population, f is the fitness value of the selected individual for implementing mutation operation, and f_{ave} is the average fitness value of all the individuals in the population.

When each node in the individual is associated with a positive integer, the position of mutation is identified by:

$$L_{mt} = \mathrm{int}[(n-1)P_{mt} + 1] \tag{4.9}$$

In the above equation, int[] is the function that converts the random real number to its closest integer, n is the number of the nodes in the selected individual for mutation, and P_{mt} is a random number between 0 and 1. L_{mt} is the position number of the root node of the sub-tree in the individual for mutation.

The mutation operation position should satisfy the following conditions:

- The node at the selected location (i.e., the root node of a sub-tree) should not be the root node of the product AND/OR tree.
- The node at the selected location should have an OR relation with other nodes in the product AND/OR tree.

If the position of the selected node cannot meet the mutation conditions, the location can be moved forward or backward along the selected individual's list step by step until the position can satisfy the conditions. Once the selected node is replaced by the other node in the AND/OR tree, a new offspring product individual is generated in the next generation.

In Figure 4.6, individual *C* (generated from Figure 4.4) is considered for mutation operation. The sub-node 'Casement' in the tree of *C* has an OR relation with the sub-node 'Picture' in the product AND/OR tree (shown in Figure 4.4). So 'Casement' can satisfy the conditions of mutation operation. 'Casement' is replaced by the 'Picture' node for creating a new child individual *C'*.

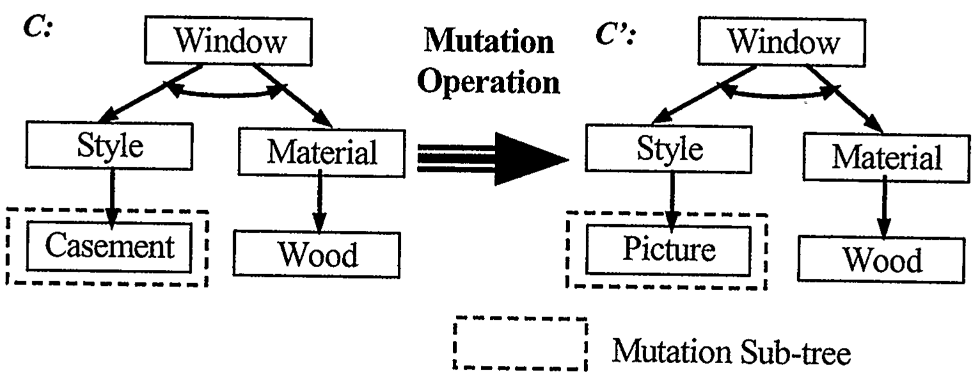


Figure 4.6 Mutation operation

Reproduction, crossover and mutation are the three operations of genetic programming for evolving a generation of solutions to a generation of better solutions. Among them, reproduction is conducted based on the fitness measures of individuals. The individuals with larger fitness values have more opportunities to be duplicated in the next generation. Crossover and mutation operations are employed for providing large varieties of solutions to achieve the optimal solution.

4.4 Parametric Optimization through Constrained Optimization

Each of the individuals in genetic programming, representing a design configuration, is modeled by design parameters. In this research, the optimal design parameter values are achieved through numerical optimization using the overall customer satisfaction index as the objective function. The best overall customer satisfaction index, corresponding to the optimal design parameters, is selected as the fitness of the design configuration for genetic programming.

In this research, the constraints for parameters are also considered in parameter optimization. For example, the length and width of a window product should only be selected between the pre-defined minimum and maximum values. Therefore, the parameter optimization problem belongs to constrained optimization problem. In this work, penalty function is selected to convert a constrained optimization problem into an unconstrained optimization problem.

Suppose the product configuration, P, is defined by its parameters (X_1, X_2, ..., X_n), the optimal parameter values considering one product configuration are obtained using constrained optimization approach:

$$\underset{w.r.t.\, X_1, X_2, \cdots X_n.}{Max} I(X_1, X_2, \cdots X_n) \tag{4.10}$$

Subject to:

$$X_{iL} \le X_i \le X_{iU}, i = 1,2,\cdots,n$$

$$h_i(X_1, X_2, \cdots, X_n) = 0, i = 1,2,\cdots,k$$

$$g_i(X_1, X_2, \cdots, X_n) \le 0, i = k+1, k+2, \cdots, m$$

where $I(X)$ is the overall customer satisfaction index. The optimal objective function evaluation measure, $I_i(P_i^*)$, is selected as the fitness of the individual representing the product configuration.

The constrained optimization problem is usually converted into an unconstrained problem. In this research, a penalty term is added to the objective function to convert the constrained optimization problem into an unconstrained optimization problem (Arora 1989). The modified objective function with a penalty term is modeled by:

$$\phi(X_1,X_2,\cdots,X_n)=I(X_1,X_2,\cdots,X_n)-\alpha\cdot\rho(X_1,X_2,\cdots,X_n) \tag{4.11}$$

where, $\rho(X_1,X_2,\cdots,X_n)$ is the penalty term, and α is a multiplier constant that determines the magnitude of the penalty. The penalty term is defined by:

$$\rho(X_1,X_2,\cdots,X_n)=\sum_{i=1}^{k}[h_i(X_1,X_2,\cdots,X_n)]^2$$

$$+\sum_{i=k+1}^{m}[g_i(X_1,X_2,\cdots,X_n)+\left|g_i(X_1,X_2,\cdots,X_n)\right|]^2 \tag{4.12}$$

After a configuration is created by genetic programming, the relevant parameters of the configuration are then optimized through the constrained optimization method. The fitness measure of a particular configuration is achieved by calculating the best overall customer satisfaction index through optimization.

In this research, each configuration created in the evolution process is described by a collection of the nodes in the product modeling tree. These nodes are further described by the parameters. For every configuration, parameters optimization is conducted for identifying the optimal parameter values of this configuration. The best objective function measure obtained through multi-objective optimization is used as the fitness measure of the corresponding configuration.

4.5 Summary

In this chapter, the optimal product design in OKP is modeled by a multi-level and multi-objective optimization problem. By introducing the overall customer satisfaction index function, the problem becomes a two level optimization problem, i.e. an optimal product configuration is first selected at the configuration level and then the best or rational parameter values for a selected product configuration are further determined at the parameter level. At the configuration level, the genetic programming is used to search for an optimal product configuration from a product family which is modeled by an AND/OR tree. At the parameter level, the constraint based mathematical optimization method is employed for parameter optimization. Various design evaluation measures, including performance measures and cost measures, are selected as objective functions for identifying the optimal product design that best meets the various customer requirements. By the overall customer satisfaction index function, these optimization objectives are integrated into a single constrained optimization problem which aims at maximizing the overall customer satisfaction.

CHAPTER 5: IMPLEMENTATION AND CASE STUDY

Based on the methods as introduced in Chapters 3 and 4, a prototype of computer-aided product design system, named Optimal OKP Product Design System, was developed through this thesis work. Industrial case studies were also conducted to demonstrate the effectiveness of the introduced approach by using the data provided by Gienow Windows and Doors Ltd. in Calgary.

5.1 Implementation of the Optimal OKP Product Design System

To improve efficiency and reduce lead time in one-of-a-kind production (OKP), the OKP companies are actively developing and adopting computer aided and integrated engineering and management technologies and systems, such as computer aided acquisition of customer requirements or computer aided customer interface, knowledge-based computer aided product design system (e.g. so-called resource engine in Gienow), Enterprise Resource Planning (ERP) or Manufacturing Resource Planning (MRP II) system for inventory management, etc. The computer-aided optimal OKP product design system, which has been developed through this thesis work, aims at identifying the optimal product design from existing OKP product families by using the methods as presented in Chapters 3 and 4.

5.1.1 Requirements for Developing the Optimal OKP Product Design System

The technical features or requirements of the optimal OKP product design system were obtained through careful study on activities of OKP product design. These technical features or requirements are summarized as follows.

- The OKP product families for modeling variations of product configurations and parameters should be described.

- The customer requirements, including performance and costs as well as their importance measures, should be modeled. The relations between design configurations/parameters and performance/cost measures should also be described.

- The multi-level and multi-objective optimization mechanism for identifying the optimal product configuration and its parameters based on the requirements of individual customers should be modeled.

- The user interface browsers to obtain the requirements of customers and show the results of the identified optimal product should be provided.

5.1.2 Architecture of the Optimal OKP Product Design System

The optimal OKP product design system was developed by using Microsoft Visual C++ 6.0 environment based on the technical features or requirements as mentioned in Section 5.1.1. Visual C++ was employed due to its capabilities of object-oriented programming and large library of Microsoft Foundation Classes (MFC).

Figure 5.1 shows architecture of the optimal OKP product design system. This system is composed of three major sub-systems, a user interface sub-system, a design evaluation and optimization sub-system, and a product database management sub-system.

1. The User Interface Sub-system

The user interface sub-system is used to define customer requirements, start the design optimization, and show the customized design result.

- Customer requirements are defined by performance measures and cost measures, as well as weighting factors of these measures.

- Optimization parameters include population size, crossover probability, mutation probability, and the maximum generation of population used in genetic programming.

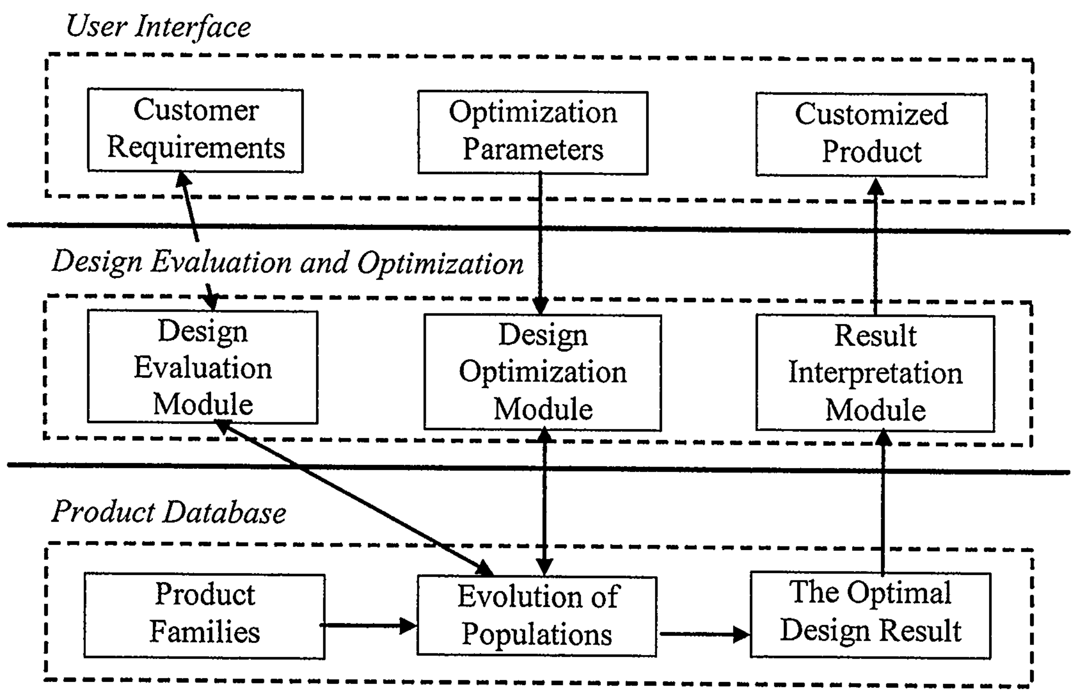


Figure 5.1 Architecture of the optimal OKP product design system

- Customized product is described by the identified design configuration and its design parameters.

2. The Design Evaluation and Optimization Sub-system

The design evaluation and optimization sub-system is used for evaluating the created design configurations and parameters in design optimization, identifying the optimal design configuration and parameters through the multi-level and multi-objective optimization approach, and interpreting the optimization result to the customer.

- Design evaluation module is used to define the relations between design configurations/parameters and performance/cost measures. The non-linear relations between evaluation measures and evaluation indices, as well as weighting factors of the selected evaluation indices are also modeled using this module.

- Design optimization module is employed for identifying the optimal design configuration and its parameters through the genetic programming and constrained optimization methods.

- The result interpretation module converts the coded optimization result created in genetic programming and constrained optimization into the format that can be understood by the customer.

3. The Product Database Management Sub-system

The product database management sub-system is used for manipulating different databases of this optimal OKP product design system, including the product family database, the generations of populations created in genetic programming, and the final optimization result.

- Product families are described by AND/OR trees for modeling the variations of product configurations and parameters.

- The intermediate results of genetic programming are described by generations of populations. Each generation is composed of individuals representing the design configurations. Each configuration is modeled by design parameters and its evaluation measures.

- The optimal design result is described by the optimal design configuration and its parameter values identified through the multi-level and multi-objective optimization.

Figure 5.2 shows a snapshot of the implemented system. The browser of the Optimal OKP Product Design System is composed of 4 areas.

- Genetic programming (GP) parameter definition area:

  This area is used to define the genetic programming parameters, including the population size, the maximum generation to run, the probability of the crossover

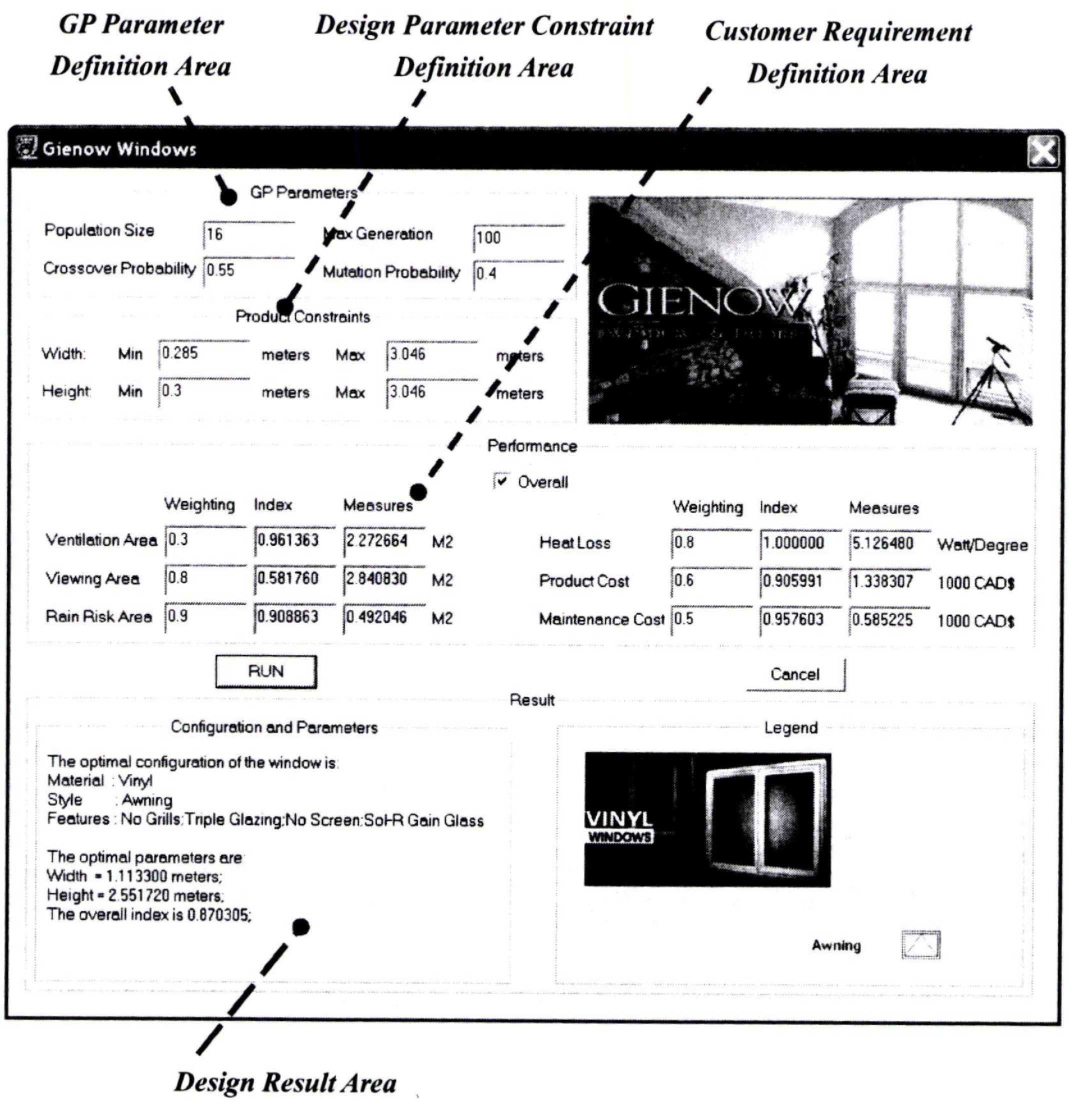


Figure 5.2 A snapshot of the optimal OKP product design system

operation, and the probability of the mutation operation. These parameters are defined by a design engineer.

- Design parameter constraint definition area:

  This area is used to define the maximum and minimum values of the design parameters. These maximum and minimum values are considered as constraints in the optimization process.

- Customer requirement definition area:

  The weighting factors of the selected evaluation measures should be defined in this area. In addition, the evaluation measures and evaluation indices of the identified optimal design are also shown in this area.

- Design results area:

  This area shows the optimal design result modeled by the optimal design configuration and its parameter values. The overall customer satisfaction index is also given in this area.

5.2 Case Study

In this research, the customized window products at Gienow Windows and Doors Ltd. are used as the examples to identify the optimal design from the product family by using the methods which have been developed through this thesis work. The optimal OKP product design system is employed to achieve the solutions of the optimal window design.

5.2.1 Window Products at Gienow

Gienow Windows and Doors Ltd. is a manufacturing company that produces windows and doors according to the individual customer requirements. These windows and doors are typical OKP products. In the past decades, a sophisticated computer system has been developed to model the OKP products based on customer needs, to create requirements of materials, machines, and personnel, and to identify the optimal production schedule. The lead-time from a customer order to the product delivery has been reduced to three weeks compared with the average of two months in this industry.

In this research, a family of the Gienow's window products is modeled by using an AND/OR tree. From this OKP product family model, the optimal window design can be identified according to the individual customer requirements.

Table 5.1 shows the major window products at Gienow. The windows are primarily classified into categories of casement, awning, picture, and slider. These different styles of the window are shown in Figure 5.3. In Gienow, different kinds of materials are used for manufacturing windows. These materials include clad, wood, and vinyl. Many different optional features, such as grills, triple glazing, screens, energy efficient glasses, safety glasses, and so on, are also provided in window products. The characteristics of these windows and their options are summarized in Table 5.1 as well.

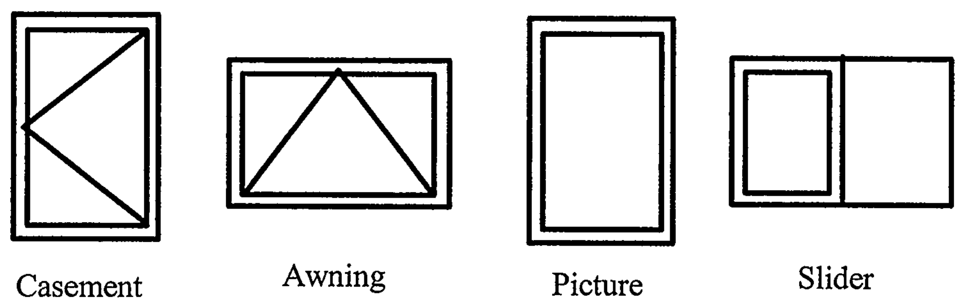


Figure 5.3 Different styles of the windows in Gienow

Despite the progress at Gienow, selection of the product configuration and its parameters from requirements of a customer is conducted manually by a sales person at Gienow. Due to the large variation of window products, usually the selected product by the sales person is not the optimal one to satisfy the requirements of the customer. Therefore, a computer system to identify the optimal product based on the requirements from customers needs to be developed. Since multiple requirements in different aspects (e.g., performance and cost) are usually specified by customers, multi-objective optimization approach should be applied to model the customer requirements in those aspects for evaluating the window products and identifying the optimal one.

Table 5.1 Window products in Gienow

Categories			Characteristics
Styles		Casement	Provide an unobstructed view. Add light, ventilation and elegance to any room. Open at least 90 degrees, making it easy to keep the view of the outdoors clean and clear.
		Awning	Let the air, not the rain (because the open degree of the awning can avoid the rain coming into rooms) into the room with weather tight awning windows. Open from the bottom, protecting the interior of the room from the rain while letting fresh air in.
		Picture	Give you a sweeping, uninterrupted view of the world outside. Comparing with other styles of window, picture windows can add elegance, drama and light in the room.
		Slider	The simplicity and durability make them a perfect accent to a range looks, from traditional to ultra-modern.
Materials		Clad	Warmth and beauty on the inside, protection from the elements on the outside. Offer low-maintenance beauty, while the interior graces your rooms with the warmth of western pine wood.
		Wood	Create the styles and timeless beauty. Improve on nature with preservatives treating the wood for extra durability and endurance, and coat hard to reach areas with a primer coat.
		Vinyl	Extremely durable and maintain their strength and color throughout the lifespan. Virtually maintenance free, vinyl never needs painting, and will not pit, peel, rot, dry out, or corrode.
Features	Grills	With grills	Add elegance and privacy.
		Without grills	Provide unobstructed view.
	Glazing	Double glazing	Provide good energy efficiency.
		Triple glazing	Give excellent energy protection in the room.
	Screen	With screen	Protect from insects such as mosquitoes in summer season.
		Without screen	Provide unobstructed view and ventilation.
	Glass types	Normal glass	Can provide normal view with low cost.
		Sol-R gain glass	Provide the clarity and color neutrality of clear glass with some of the best performance characteristics available.
		Sol-R shield glass	Greatly reduces the amount of heat gain caused by the sun on hot days, as well as decrease heat loss on cooler days.
		Safety glass	Increase the strength by lamination.

5.2.2 Modeling of the Window Products

To identify the optimal product from the product family, the first step is to model the product family. In this research, AND/OR trees with the parameters in the nodes of the AND/OR trees are employed to model the window product families.

The variations of window products, including variations of configurations and variations of parameters, are modeled by an AND/OR tree as shown in Figure 5.4. Each node in this AND/OR tree is further described by parameters.

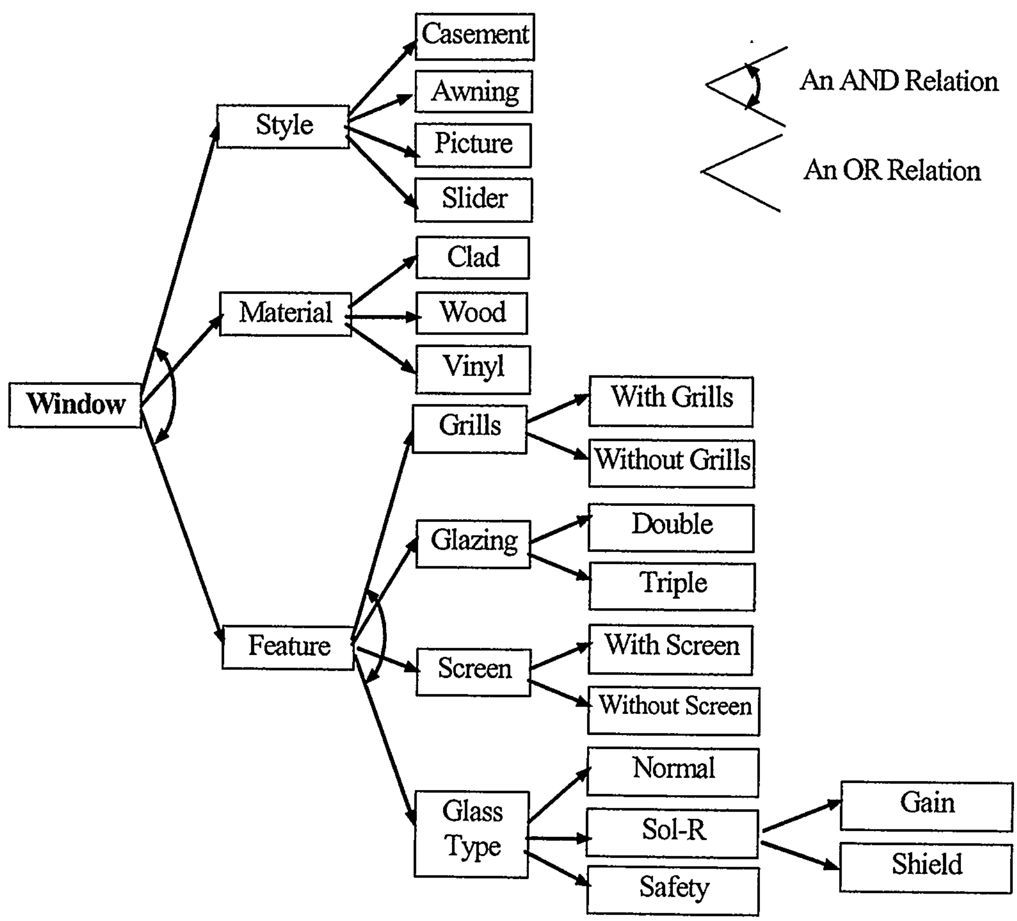
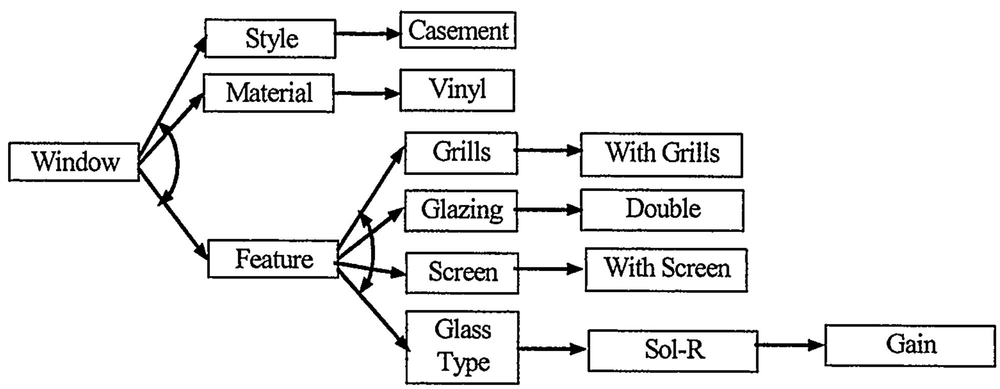


Figure 5.4 The AND/OR tree for modeling configuration variations of the windows

A feasible window product configuration is created from the AND/OR tree using the method introduced in Chapter 3. Since each of the nodes in the AND/OR tree is defined by parameters, a window product configuration is then described by a number of parameters. A feasible window product (configuration and its relevant parameters) created from the AND/OR tree is shown in Figure 5.4.



(a) A window product configuration

Width = 1.2 m

Height = 0.9 m

Color = "beige"

OpeningDirection = "right"

GrillBarSize = 5/16 inches

GrillBarColor = "beige"

... ...

(b) Parameters of the selected window product configuration

Figure 5.5 A customized window product (with configuration and its parameters)

In the product configuration shown in Figure 5.5, window style (casement), material (vinyl), and features (with grills, double glazing, with screen, Sol-R gain glass) are all defined based on the product AND/OR tree model. Parameters of the configuration are described as: width 1.2 *m*, height 0.9 *m*, beige color, right open direction, 5/16 *inches* of grill bars, etc.

5.2.3 Modeling of Customer Requirements

Customer requirements are modeled by evaluation measures of the products. The methods for modeling customer requirements introduced in Chapter 3 are employed in this case study.

Six product evaluation measures are selected in this case study to evaluate the window products according to the customer requirements. Among the six evaluation measures, there are four performance evaluation measures and two cost evaluation measures. These measures are: ventilation area, viewing area, rain risk area, heat loss, product cost and maintenance cost. These evaluation measures are selected to evaluate a window product configuration and its parameters. Table 5.2 summarizes these window products evaluation measures.

Table 5.2 Product evaluation measures

Evaluation measures		**Units**	**Symbols**
Performance measures	Ventilation area	Square meters (m^2)	P_{vent}
	Viewing area	Square meters (m^2)	P_{view}
	Rain risk area	Square meters (m^2)	P_{rain}
	Heat loss	Watt per degree ($W/^oC$)	P_{heat}
Cost measures	Product cost	Canadian dollars ($\$$)	C_p
	Maintenance cost	Canadian dollars ($\$$)	C_m

In Table 5.2, the six evaluation measures, their units, the symbols of these measures used in this thesis are included.

5.2.3.1 Ventilation Area (P_{vent})

Ventilation area is the effective area for allowing the air to flow into the room. The ventilation area is calculated by equation given in Table 5.3.

Table 5.3 Calculation of ventilation area P_{vent} (m^2)

Style	Screen	Calculation equations
Casement	With screen	$P_{vent} = \alpha \times W \times H$
Casement	Without screen	$P_{vent} = W \times H$
Awning	With screen	$P_{vent} = \beta \times \alpha \times W \times H$
Awning	Without screen	$P_{vent} = \beta \times W \times H$
Slider	With screen	$P_{vent} = 0.5 \times \alpha \times W \times H$
Slider	Without screen	$P_{vent} = 0.5 \times W \times H$
Picture	With screen	$P_{vent} = 0$
Picture	Without screen	$P_{vent} = 0$

where, W: width; H: height;

α: screen factor ($\alpha = 0.95$); β: awning factor ($\beta = 0.85$)

To calculate the ventilation area, only some of the nodes in the AND/OR tree, such as styles of the windows, with or without screen in features, have the relations with the ventilation area.

5.2.3.2 Viewing Area (P_{view})

Viewing area represents the effective area for viewing the outside scenery through the window. Viewing area is calculated by the equations provided in Table 5.4. From this table, it is clear that only the window styles, screen and grills are related to the viewing area.

Table 5.4 Calculation of viewing area P_{view} (m^2)

Style	**Screen**	**Grills**	**Calculation equations**
Casement/Awning/Slider	Without screen	Without grills	$P_{vent} = W \times H$
Casement/Awning/Slider	With screen	Without grills	$P_{vent} = \alpha \times W \times H$
Casement/Awning/Slider	Without screen	With grills	$P_{vent} = \beta \times W \times H$
Casement/Awning/Slider	With screen	With grills	$P_{vent} = \alpha \times \beta \times W \times H$
Picture	Without screen	Without grills	$P_{vent} = W \times H$
Picture	Without screen	With grills	$P_{vent} = \beta \times W \times H$

where, W: width; H: height;

α: screen factor (α=*0.95*); β: grill factor (β=*0.85*)

5.2.3.3 *Rain Risk Area (P_{rain})*

Rain risk area is defined as the area that rain can possibly come into the room when the window is accidentally left open. The rain risk area is calculated by equations given in Table 5.5.

Table 5.5 Calculation of rain risk area P_{rain} (m^2)

Style	**Calculation equations**
Casement	$P_{rain} = \alpha \times W \times H$
Awning	$P_{rain} = \alpha \times \beta \times W \times H$
Slider	$P_{rain} = 0.5 \times \alpha \times W \times H$
Picture	$P_{rain} = 0$

where, W: width; H: height;

α: rain risk factor (α=*0.58*);

β: rain risk correction factor for awning window (β=*0.30*).

5.2.3.4 <u>*Heat Loss (P_{heat})*</u>

Heat loss of the window is caused by the heat loss of the frame and the heat loss of the glass. This evaluation measure is considered important by customers for both the hot days and the cold days. A low heat loss measure can prevent the heat from the outside in hot days, while keeping the heat of the room in cold days. The total heat loss of the window is calculated by:

$$P_{heat} = P_{heat-frame} + P_{heat-glass} \tag{5.1}$$

The heat loss is measured by unit of watt per degree of the temperature difference between the inside and outside surfaces of the window. The heat loss caused by the frame is calculated by the equations given in Table 5.6.

Table 5.6 Calculation of heat loss caused by the frame $P_{heat\text{-}frame}$ (W/°C)

Style	Material	Calculation equations
Casement/Awning/Picture	Clad	$P_{heat\text{-}frame} = C_{clad} \times \alpha \times W \times H$
Casement/Awning/Picture	Wood	$P_{heat\text{-}frame} = C_{wood} \times \alpha \times W \times H$
Casement/Awning/Picture	Vinyl	$P_{heat\text{-}frame} = C_{vinyl} \times \alpha \times W \times H$
Slider	Clad	$P_{heat\text{-}frame} = C_{clad} \times \beta \times W \times H$
Slider	Wood	$P_{heat\text{-}frame} = C_{wood} \times \beta \times W \times H$
Slider	Vinyl	$P_{heat\text{-}frame} = C_{vinyl} \times \beta \times W \times H$

where, W: width of the window;

H: height of the window;

α: casement/awning/picture factor (α=1/35);

β: slider factor (β=1/30);

C_{clad}: heat loss coefficient of clad (C_{clad}=180W/(m^2 °C));

C_{wood}: heat loss coefficient of wood (C_{wood}=0.24W/(m^2 °C));

C_{vinyl}: heat loss coefficient of vinyl (C_{vinyl}=0.16 W/(m^2 °C)).

The heat loss caused by the glass is calculated by the equations given in Table 5.7.

Table 5.7 Calculation of heat loss caused by the glass $P_{heat\text{-}glass}$ (W/°C)

Glazing	Glass type	Calculation equations
Double	Normal/Safety	$P_{heat\text{-}glass} = C_{double} \times W \times H$
Double	Sol-R	$P_{heat\text{-}glass} = C_{double} \times \alpha \times W \times H$
Triple	Normal/Safety	$P_{heat\text{-}glass} = C_{triple} \times W \times H$
Triple	Sol-R	$P_{heat\text{-}glass} = C_{triple} \times \alpha \times W \times H$

where, W: width; H: height; α: energy saving factor $(\alpha = 80\%)$;

C_{double}: heat loss coefficient of double glazing ($C_{double} = 2.5\ W/(m^2\,^{o}C)$);

C_{triple}: heat loss coefficient of triple glazing ($C_{triple} = 1.8\ W/(m^2\,^{o}C)$).

5.2.3.5 Product Cost (C_p)

Cost of product is obtained from the Gienow product catalogue. The cost measures are determined by the configurations of styles, materials, features of the window, and the relevant attributes of the window products. The product costs are modeled by a sophisticated database system at Gienow. Product costs are described with unit of Canadian Dollars.

5.2.3.6 Maintenance Cost (C_m)

In this case study, the cost for painting the frame of the window and the cost for minor repairs of the frame within the twenty years of the window product life span are selected as the maintenance cost. The maintenance cost is calculated by equations given in Table 5.8. From this table, we can see usually for the same sized window, the clad windows need the minimum maintenance. The wood windows require frequent painting of the frames to protect the wood against the rain, snow and so on. The vinyl windows need some repair work towards the end of the product life span.

Table 5.8 Calculation of the maintenance cost C_m (CAD\$)

Material	Calculation equations
Clad	$C_m = 21 \times W \times H + 90$
Wood	$C_m = 160 \times W \times H + 1000$
Vinyl	$C_m = 30 \times W \times H + 500$

where, *W*: width of the window;

H: height of the window.

5.2.4 Modeling of the Relations between Evaluation Measures and Evaluation Indices

Since the six product evaluation measures have different units, it is required that these six product evaluation measures should be converted into comparable product evaluation indices using the methods introduced in Chapter 3. In this research, the customer satisfaction index is employed to evaluate the product design. Since the values of the customer satisfaction are set between 0 and 1 without units, these values can be used to compare with each other for evaluating the product design. In Table 5.9, the six evaluation measures and corresponding customer satisfaction indices in pairs are shown.

Based on the given points with the evaluation measures and the relevant indices, the least-square curve-fitting method is employed to achieve the continuous non-linear relations between evaluation measures (*P*s and *C*s) and their evaluation indices (*I*s). In this case study, the six non-linear relations are summarized in Equations (5.2)-(5.8). These equations are obtained through mapping the relations between the evaluation measures and the customer satisfaction indices using the data in Table 5.9.

Table 5.9 Evaluation measures and their indices

P_{vent} (m^2)	0.15	0.3	0.5	0.8	1.0	1.5	1.8	2.0
I_{vent}	0.06	0.32	0.58	0.82	0.90	0.958	0.962	0.985

P_{view} (m^2)	1	2	3	4	5	7	8	9
I_{view}	0.05	0.4	0.6	0.8	0.9	0.96	0.97	0.99

P_{rain} (m^2)	0	0.4	0.5	0.64	0.7	0.77	0.86	1
I_{rain}	1	0.95	0.9	0.8	0.7	0.6	0.4	0.1

P_{heat} (W)	5	18	25	40	55	70	82	85
I_{heat}	1	0.9	0.8	0.6	0.4	0.2	0.1	0.05

C_p (CAD$)	250	750	1000	1500	1750	2000	2500	3000
I_p	1	0.9	0.85	0.7	0.6	0.5	0.35	0.25

C_m (CAD$)	250	750	1000	1500	1750	2000	2500	3000
I_m	1	0.9	0.85	0.7	0.6	0.5	0.35	0.25

$$I_{vent} = 0.3209P_{vent}^3 - 1.4994P_{vent}^2 + 2.3318P_{vent} - 0.2486 \quad (5.2)$$

$$I_{view} = 0.0022P_{view}^3 - 0.0561P_{view}^2 + 0.4723P_{view} - 0.3510 \quad (5.3)$$

$$I_{rain} = -1.5035P_{rain}^3 + 0.7861P_{rain}^2 - 0.2013P_{rain} + 0.9967 \quad (5.4)$$

$$I_{heat} = 1.3264P_{heat}^3 - 1.8P_{heat}^2 - 0.5645P_{heat} + 1.0442 \quad (5.5)$$

$$I_p = 0.043C_p^3 - 0.2133C_p^2 - 0.006C_p + 1.0213 \quad (5.6)$$

$$I_m = 0.043C_m^3 - 0.2133C_m^2 - 0.006C_m + 1.0213 \quad (5.7)$$

Figure 5.6 shows the curves representing the non-linear relations between the evaluation measures and the evaluation indices.

5.2.5 Identification of the Optimal Product Configuration and Its Parameters

The optimal individual window product (configuration and its parameters) is identified using the methods introduced in Chapter 4. In this case study, the optimal product configuration is achieved through genetic programming, while the optimal parameters for each configuration are obtained through constrained optimization.

The optimization objective function considering the six evaluation indices is formulated using the multi-objective optimization approach by assigning weighting factors to these evaluation indices. This objective function is given by:

$$Max\ I = \frac{0.3I_{vent} + 0.8I_{view} + 0.9I_{rain} + 0.8I_{heat} + 0.6I_{p} + 0.5I_{m}}{0.3+0.8+0.9+0.8+0.6+0.5} \tag{5.8}$$

The multi-level optimization process is started by creating the first generation of the individuals representing feasible product configurations. Each individual is created randomly from the AND/OR tree given in Figure 5.4. In this case study, the population size of each generation is selected as 16. The 16 individuals created in the first generation are given in Table 5.10.

Each of the individuals for modeling a product configuration is described by parameters. In this case study, only two continuous parameters, the width *(W)* and height *(H)* of the window, are considered. For each individual in a generation, constrained optimization is employed to identify the optimal parameter values for achieving the maximum overall customer satisfaction index defined in Equation (5.8). For example, the multi-objective optimization considering the product configuration described by individual 1, P = {Vinyl, Awning, Grills, Double glazing, No screen, Normal glass}

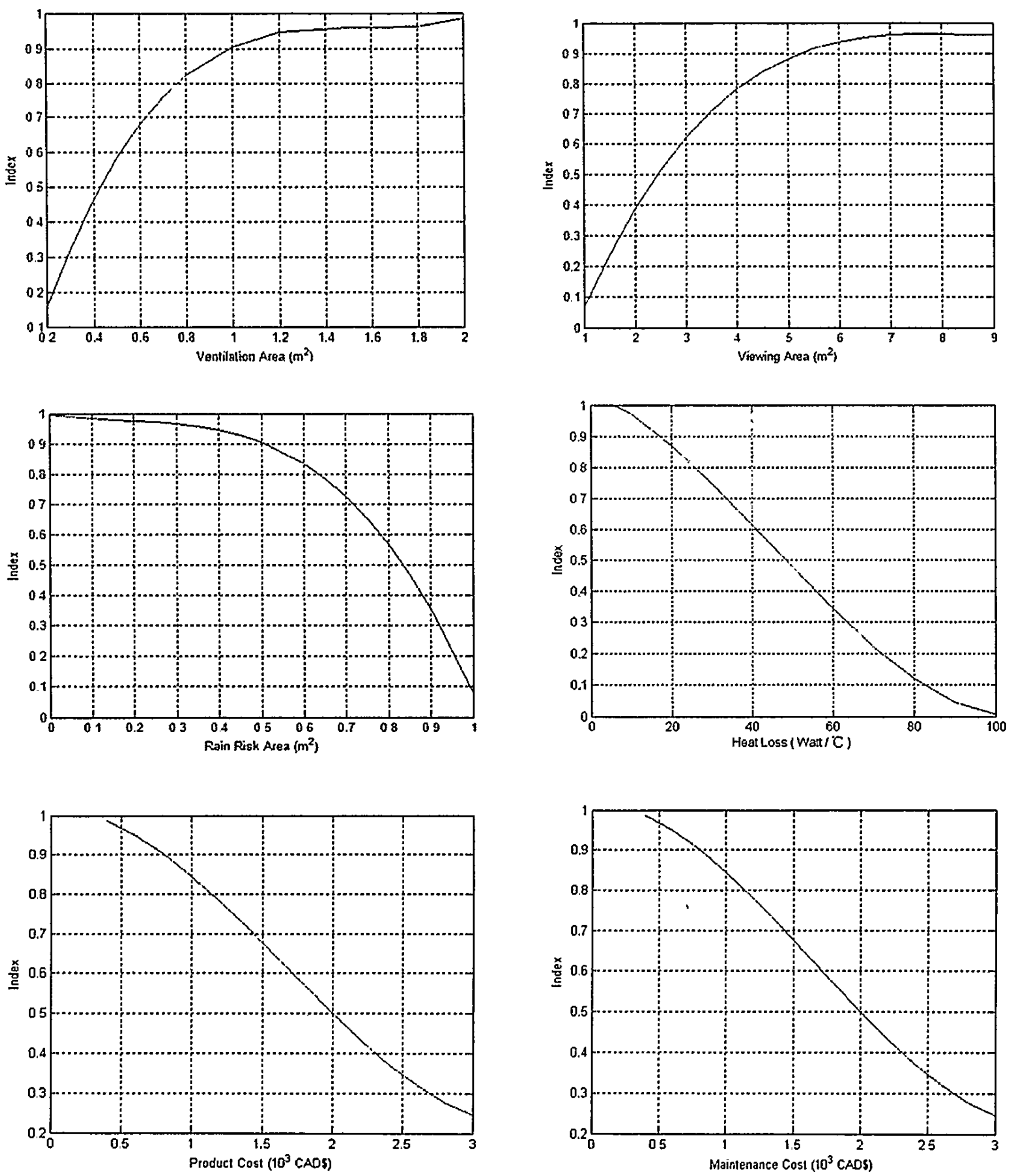


Figure 5.6 Non-linear relations between evaluation measures and evaluation indices

in the first generation shown in Table 5.10 is formulated as:

$$\underset{w.r.t.\ W,H}{Max}\ I(W,H) \tag{5.9}$$

Subject to:

$$0.285 \le W \le 3.046$$

$$0.3 \le H \le 3.046$$

For this configuration, the optimal parameters are achieved as using constrained optimization:

$$W^* = 2.94\ \text{(m)}$$
$$H^* = 0.9\ \text{(m)}$$

The best overall customer satisfaction index I^* for this product individual (the product configuration with the optimal parameter values) is identified as

$$I^* = 0.856$$

This index is used as the fitness measure of this individual. The optimal parameter values and the fitness measure for each of all the 16 individuals in the first generation are given in table 5.10. The average fitness of this generation is calculated as 0.798.

Evolution of the product individuals from one generation to the next generation is conducted by applying the three operations of genetic programming to reach the optimal configuration and its parameters. These three operations are: reproduction, crossover, and mutation. The algorithm used in the evolution process is introduced in Section 4.3.

Reproduction is started by selecting two parent individuals in the current generation according to their fitness measures using the roulette wheel selection method. In this case

Table 5.10 First generation for genetic programming

Individual number	Configuration of window	Parameters (m)		Fitness	Number of copies
		W	*H*		
1	Vinyl, Awning, Grills, Double Glazing, No Screen, Normal Glass	2.94	0.9	0.856	1
2	Wood, Picture, Grills, Triple Glazing, Screen, Normal Glass	1.75	2.5	0.817	0
3	Vinyl, Picture, No Grills, Triple Glazing No Screen, Normal Glass	1.75	2.99	0.85	1
4	Wood, Casement, Grills, Triple Glazing, No Screen, Sol-R Shield Glass	0.81	1.45	0.71	1
5	Wood, Awning, No Grills, Double Glazing, No Screen, Sol-R Shield Glass	1.5	1.76	0.861	1
6	Wood, Slider, Grills, Double Glazing, Screen, Normal Glass	1.11	1.56	0.64	0
7	Wood, Awning, Grills, Triple Glazing, No Screen, Normal Glass	1.53	1.78	0.848	2
8	Vinyl, Slider, No Grills, Triple Glazing, No Screen, Normal Glass	0.89	2.03	0.781	2
9	Vinyl, Picture, Grills, Double Glazing, No Screen, Sol-R Shield Glass	2.3	2.17	0.835	1
10	Wood, Picture, Grills, Double Glazing, No Screen, Normal Glass	1.53	2.77	0.813	2
11	Wood, Picture, No Grills, Double Glazing, No Screen, Normal Glass	2.49	1.73	0.82	1
12	Clad, Picture, No Grills, Triple Glazing, No Screen, Sol-R Gain Glass	1.8	1.76	0.797	2
13	Wood, Slider, No Grills, Triple Glazing, No Screen, Sol-R Gain Glass	0.75	2.41	0.659	0
14	Vinyl, Picture, Grills, Triple Glazing, No Screen, Sol-R Shield Glass	2.99	1.73	0.839	1
15	Wood, Awning, Grills, Triple Glazing, Screen, Normal Glass	2.25	1.59	0.833	1
16	Vinyl, Picture, No Grills, Double Glazing, Screen, Sol-R Shield Glass	1.91	2.63	0.841	0
Average fitness of the generation				0.798	

study, two random numbers of 0.492 and 0.623 are generated first and the 8th individual and the 10th individual in Table 5.10 are selected based on Equation (4.2). The selected two individuals are given in Figure 5.7. The crossover operation and the mutation operation are then considered for these two parent individuals to form the two individuals in the second generation. This evolution process is continued until the number of the individuals in the second generation also reaches to 16, the same as the first generation.

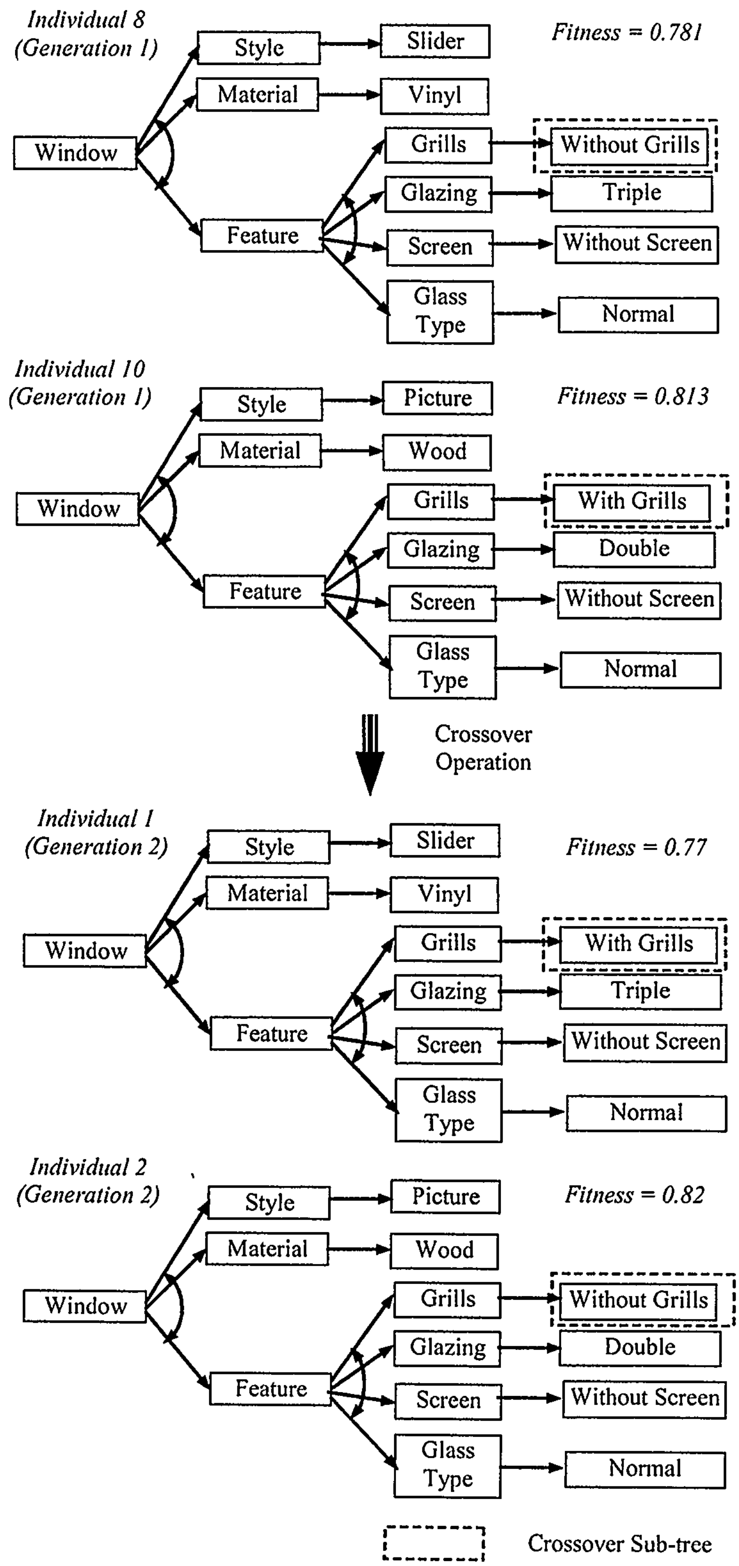


Figure 5.7 Crossover operation

The crossover operation is considered first for the two selected individuals after reproduction. In this case study, the threshold crossover probability $p_{cs}^{(t)}$ is pre-defined as 0.55. The crossover probability, p_{cs}, is obtained using Equation (4.6).

$$p_{cs} = (f_{\max} - f_{bigger})/(f_{\max} - f_{ave}) = (0.861 - 0.813)/(0.861 - 0.798) = 0.762 \quad (5.10)$$

Since the crossover probability, p_{cs}, is larger than the threshold crossover probability, $p_{cs}^{(t)}$, the crossover operation is then applied to these two selected individuals. First, the positions of the crossover nodes in these two individuals are selected using Equation (4.7). The two nodes labelled with dashed boxes, having an OR relation between them in the AND/OR tree, are swapped to form two new individuals in the second generation shown in Figure 5.7.

The mutation operation is then considered for each of the two individuals after the crossover operation has been completed. In this case study, the threshold mutation probability $p_{mt}^{(t)}$ is pre-defined as 0.4. The mutation probabilities p_{mt} are obtained using Equation (4.8).

$$p_{mt,1} = 0.5 \quad (5.11)$$

$$p_{mt,2} = 0.5(f_{\max} - f)/(f_{\max} - f_{ave}) = 0.5(0.861 - 0.82)/(0.861 - 0.798) = 0.317 \quad (5.12)$$

Since the mutation probability, $p_{mt,1}$ is larger than the threshold mutation probability $p_{mt}^{(t)}$ (predefined as 0.4), the mutation operation is then applied to individual 1. The position of the mutation node in this individual is selected using Equation (4.9). This node is labelled with a dashed box in Figure 5.8. Because the selected node 'Normal' has an OR relation with another node 'Sol-R→Gain' in the AND/OR tree, this node ('Normal') is replaced by another node ('Sol-R→Gain') in the AND/OR tree to form a new individual in the second generation shown in Figure 5.8. For individual 2, since $p_{mt,2}$ is smaller than the threshold mutation probability, $p_{mt}^{(t)}$, the mutation operation is not applied to the individual 2. The individual 2 is moved directly to the second generation.

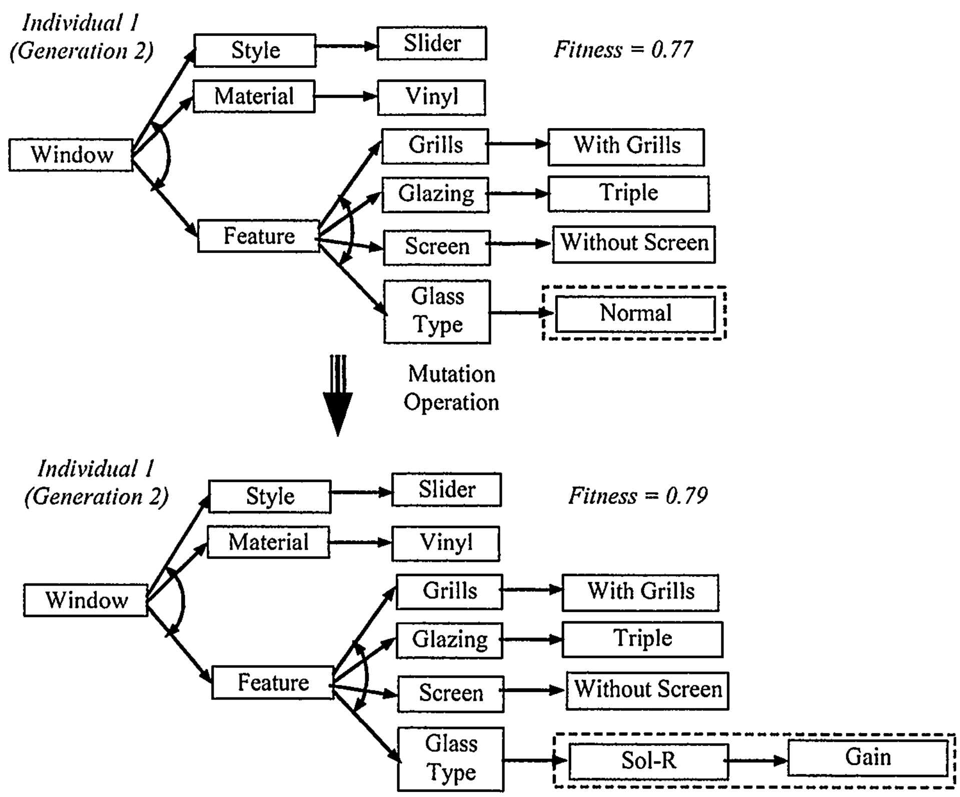


Figure 5.8 Mutation operation

In the same way, a total of 16 new individuals are created in the second generation from the first generation, as shown in Table 5.11. From this table, the average fitness of the 16 individuals has been improved to 0.808, which is better than the average fitness of the first generation. The evolution process of genetic programming is continued until the final optimal result is achieved. In this case study, 30 generations of individuals are created to identify the optimal product configuration and its parameter values. The average fitness measures (i.e., the average overall customer satisfaction indices) of these 30 generations are shown in Figure 5.9.

Table 5.11 Second generation for genetic programming

Individual number	Window's configuration	Parameters (m)		Fitness
		W	*H*	
1	Vinyl, Slider, Grills, Triple Glazing, No Screen, Sol-R Gain Glass	2.3	0.77	0.79
2	Wood, Picture, No Grills, Double Glazing, No Screen, Normal Glass	2.49	1.73	0.82
3	Vinyl, Picture, Grills, Triple Glazing, No Screen, Normal Glass	2.99	1.73	0.839
4	Clad, Awning, Grills, Double Glazing, No Screen, Normal Glass	1.17	2.14	0.832
... ...	... ...	... ...	... ...	... ...
Average fitness of the generation				0.808

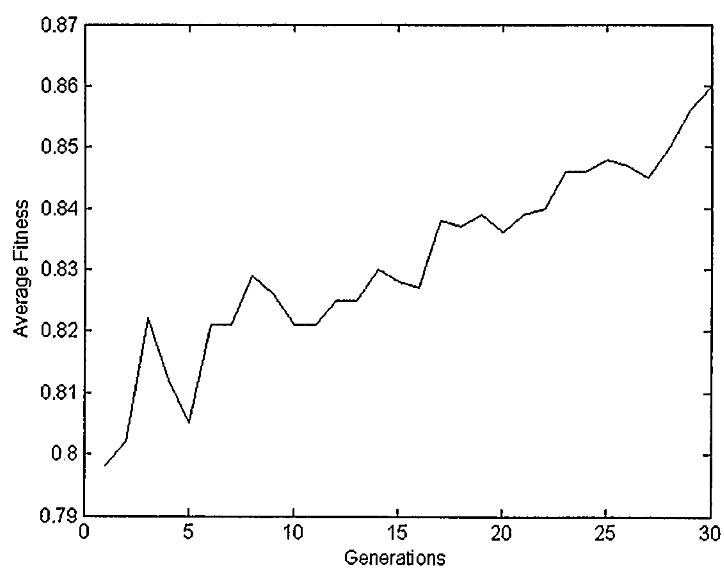


Figure 5.9 The average fitness measures of 30 generations

The optimal product is identified as:

- The optimal configuration:

Vinyl, Awning, No grills, Triple glazing, No screen, Sol-R Gain Glass

- The optimal parameters:

  Width *(W)* = 1.11 *m*

  Height *(H)* = 2.55 *m*

Table 5.12 shows evaluation measures of the identified optimal window product.

Table 5.12 Evaluation of the identified optimal product

Item	**Evaluation measure**	**Evaluation index**
Ventilation area	2.27 m^2	0.96
Viewing area	2.84 m^2	0.58
Rain risk area	0.49 m^2	0.91
Heat loss	5.13 W/(°C)	1.00
Product cost	$1,338.31	0.91
Maintenance cost	$585.23	0.96
Overall evaluation index		0.87

5.2.6 Selection of Different Products Based on Different Customer Requirements

When different weighting factors are selected by different customers, the different products will be identified using the method developed in this research. Table 5.13 shows the five products identified for five customers. The product identified in Section 5.2.5 is given in the last column of this table.

Table 5.13 Different products to satisfy different requirements of customers

Product Number		1	2	3	4	5
Weighting factors	**Ventilation area**	0.9	0.1	0.1	0.1	0.3
	Viewing area	0.1	0.9	0.1	0.1	0.8
	Rain Risk area	0.1	0.1	0.1	0.1	0.9
	Heat loss	0.1	0.1	0.9	0.1	0.8
	Product cost	0.1	0.1	0.1	0.9	0.6
	Maintenance cost	0.1	0.1	0.1	0.8	0.5
Optimal configuration		Vinyl, Casement, Grills, Triple Glazing, No screen, Sol-R Gain Glass	Vinyl, Picture, No Grills, Triple Glazing, Screen, Normal Glass	Wood, Awning, No Grills, Triple Glazing, Screen, Sol-R Gain Glass	Clad, Picture, No Grills, Triple Glazing, Screen, Normal Glass	Vinyl, Awning, No Grills, Triple Glazing, No Screen, Normal Glass
Optimal parameters	**Width**	1.5	3.046	0.285	0.285	1.11
	Height	1.98	3.046	0.3	0.3	2.55
Customer evaluation measures	P_{vent} (m^2)	9.28	0	2.0	0	2.27
	P_{view} (m^2)	7.89	9.28	3.4	0.086	2.84
	P_{rain} (m^2)	5.36	9.28	0.62	0	0.49
	P_{heat} $(W/^oC)$	16.7	13.96	6.4	0.57	5.13
	C_p (\$)	4030	2860	1580	270	1338
	C_m (\$)	780	780	610	92	585
Customer evaluation indices	I_{vent}	0.996	0	0.96	0	0.96
	I_{view}	0.802	0.814	0.64	0	0.58
	I_{rain}	0.012	0.81	0.82	0.997	0.91
	I_{heat}	0.905	0.93	0.99	0.99	1.00
	I_p	0.223	0.71	0.88	0.97	0.91
	I_m	0.95	0.95	0.96	0.99	0.96
Overall index	I	0.93	0.81	0.992	0.982	0.87

From Table 5.13, it can be seen that when the customer pays special attention to reduce the rain risk while requiring reasonable ventilation, the awning window is usually selected. When heat loss is a major concern, triple glazing with Sol-R glass is usually identified. When maintenance cost needs to be reduced, the clad window is usually selected. The optimization results match with the results achieved based on experience of sales persons. When the variations of configurations and parameters are significantly large, this newly introduced automated optimal product configuration and parameter design system based upon quantitative evaluation can provide better result.

5.3 Summary

In this chapter, implementation of the Optimal OKP Product Design System is presented. The system was developed by using Visual C++, an object-oriented programming environment. A number of case study examples by using the data collected from Gienow are also introduced based on the methodologies as presented in Chapters 3 and 4. The feasibility and effectiveness of the developed methods and system are demonstrated by using these case study examples.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

This chapter gives the conclusions which are based on the discussion and presentation made in this thesis. The directions of future work are also outlined at the end of this chapter.

6.1 Conclusions

This thesis work aims at developing an innovative method for identifying the optimal design based on the requirements of customers in one-of-a-kind production (OKP) environment.

One-of-a-kind production, as a type of customer-oriented production mode, is becoming more and more popular in manufacturing companies, especially in the small and middle sized manufacturing companies. As discussed in Chapters 1 and 2, OKP is a new production paradigm for producing customized products based on requirements of individual customers while maintaining scales of economy in mass production along with a high standard of quality.

In Chapters 3 and 4, the multi-level and multi-objective optimal design approach for identifying the optimal product configuration and its parameters based on the requirements of individual customer on performances and costs is presented. In this thesis work, the different performance and cost measures in different units are first converted into comparable customer satisfaction indices by using the least-square curve-fitting method. These comparable indices are associated by their weighting factors identified through using the pair-wise comparison method. The optimization is conducted at two different levels, configuration optimization and parameter optimization, by using genetic programming and constrained optimization.

In Chapter 5, implementation of the optimal OKP product design system and case studies are discussed. Through these case studies, it was demonstrated that the developed system was effective for identifying the optimal customized products in terms of customer requirements.

Based on the research results, the following conclusions can be drawn:

1. The AND/OR tree is an effective scheme to model an OKP product family.

The AND/OR trees and parameters of the nodes in AND/OR trees are employed to model OKP product families in this thesis work. The variations of the OKP product configurations are modeled by the AND/OR tree. The variations of the OKP product parameters are described by the variations of node parameters. The customized product, modeled by both the design configuration and its parameters, is created from the AND/OR tree of the product family.

This design representation scheme is effective for modeling the variations of OKP products and identifying the optimal design through multi-level and multi-objective optimization.

2. The least-square curve-fitting method and pair-wise comparison method are good tools for modeling the non-linear relations between product evaluation measures and customer satisfaction indices and for achieving the weighting factors of different design evaluation measures, respectively.

A new approach is introduced in this work to associate the different evaluation measures into an integrated environment for evaluating the created design candidates. In this approach, the different design evaluation measures are converted into comparable evaluation indices representing levels of customer satisfaction in the relevant aspects. The non-linear relations between design evaluation measures and design evaluation indices are identified by using the least-square curve-fitting method. The different design evaluation measures are associated with weighting factors to integrate different evaluation aspects into the same environment. When a large number of evaluation measures are considered, the pair-wise comparison method is employed to maintain the consistency of the weighting factors.

The introduced approach is effective for modeling the non-linear relations among different design evaluation measures. This approach also converts a multi-objective optimization problem into a single-objective optimization problem for identifying the optimal design based upon customer requirements.

3. The multi-level and multi-objective optimization method is effective for identifying the optimal product configuration and parameters from customer requirements on performance and costs.

Since a customized product is modeled by both the design configuration and the design parameters, a multi-level optimization approach is developed in this research for identifying the optimal design configuration and the optimal design parameters. This optimization is conducted at two different levels, configuration optimization level and parameter optimization level and which are implemented using genetic programming and constrained optimization, respectively. Since various evaluation measures, including performance measures and costs measures from customers, are considered in this work, the multi-objective optimization method is employed to identify the optimal design considering all the relevant evaluation measures.

This multi-level and multi-objective optimization method is effective in one-of-a-kind production environment for identifying the optimal design configuration and its parameters from the product family modeled by an AND/OR tree based on the different customer requirements on performance and costs.

4. An optimal OKP product design system has been developed in this research.

An optimal OKP product design system was developed in this work based on the methods introduced in this research. This system is composed of three sub-systems, a user interface sub-system, a design evaluation and optimization sub-system, and a product database management sub-system, for manipulating various design activities in one-of-a-kind production environment. Several case studies have also been conducted using the product data obtained from Gienow to demonstrate the effectiveness of this optimal OKP product design approach.

6.2 Future Work

Although some theoretical and empirical research findings have been achieved through this thesis work, many issues still need to be further addressed for developing one-of-a-kind product design and manufacturing systems. These issues are summarized as follows.

1. Suppliers involved OKP product design systems need to be developed.

In this thesis work, only some of the aspects related to manufacturers and customers, including costs and performance, were considered to evaluate the product design. In a real one-of-a-kind production environment, suppliers also have strong influences on the quality and efficiency of product design and manufacture. Therefore, an OKP product design needs to involve both the customers and suppliers. Various types of constraints from the suppliers, including the capabilities of manufacturing functions, availability of manufacturing resources, etc., should be included at the product design stage. The involvement of suppliers may improve the competitiveness of an OKP product in marketplaces.

2. The OKP product design system developed in this thesis needs to be further improved to model more complex OKP products in the future.

In this thesis research project, only the variations of configurations and parameters of OKP products can be modeled. When other design information, such as quantitative relations and constraints among design parameters, qualitative relations among design components, functions and behaviors of design components, etc., need to be described, a more sophisticated OKP product design approach and system are then required to be developed. In addition, it is also required to link or integrate this OKP product design system with a commercial CAD system, such as SolidWorks or Pro/Engineer.

3. A computer-aided engineering system to support various OKP product development activities is needed.

This research project primarily focuses on the design aspect in one-of-a-kind production. Many other aspects of one-of-a-kind production, such as production process planning, production scheduling, production system monitoring and control, product delivery, customer services, etc., should also be considered in the future to develop a computer-aided engineering system to support these product development activities in an integrated manner.

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