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An Intelligent System for Supporting Affective Product Design

By

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Certificate of Originality

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Abstract

Affective design is currently an important aspect of new product development, especially for consumer products, to achieve a competitive edge in a marketplace. Affective design can help companies develop new products that can better satisfy the emotional needs of customers. In this research, a novel methodology for supporting the affective design of products is proposed. Through this methodology, an intelligent system is subsequently developed. The methodology primarily involves four processes, namely, survey conducting, rule mining, affective relationship modelling, and design optimisation.

First, customer affections on product design have to be collected by conducting a marketing survey. The obtained survey data are used to model the affective relationships between customer affections and the design attributes of the products. An intelligent system for supporting affective design based on the proposed methodology can be developed to perform rule mining, affective relationship modelling, and design optimisation. The system involves three models, namely, a multi-objective genetic algorithm (MOGA) based rule-mining model, a dynamic neuro-fuzzy (NF) model, and a design optimisation model.

A novel two-stage MOGA approach is proposed to perform rule mining for affective design. To consider the ambiguity of affective data, approximate rules are generated based on MOGA considering the three criteria of rule mining, including accuracy, comprehensibility, and extent of approximations. A two-stage rule-mining method is introduced to generate individual rules and subsequently refine the entire rule set considering rule interactions.

A new dynamic NF approach is proposed for affective relationship modelling based on the survey data using a modified dynamic evolving neuro-fuzzy inference system (DENFIS). DENFIS is suitable for dealing with the ambiguity of affective relationships. Moreover, DENFIS can handle a large number of input attributes and data sets, whereas conventional adaptive neuro-fuzzy inference system (ANFIS) models cannot. In the dynamic NF approach, local models are established based on the evolving clustering method. Thus, the structures of DENFIS models are simple. A recursive least square is applied on DENFIS, enabling the dynamic NF models to be updated easily once new data sets are available.

For the design optimisation model, a novel guided search genetic algorithm (GA) approach is introduced to determine optimal design attribute settings of affective design. With the use of the developed NF models and mined rules, a search strategy based on the guided search GA is formulated, resulting in the determination of better solutions of affective design and decrease in the searching time of design optimisation.

A case study of the affective design of mobile phones was conducted to illustrate the methodology and the development of the intelligent system and to validate their effectiveness. A number of important results were obtained from the validation tests. First, the MOGA-based rule-mining approach performs better than the dominance-based rough set-based rule-mining approach in terms of accuracy and reliability in mining approximate rules. Second, the dynamic NF model outperforms conventional ANFIS models in modelling affective relationships. Third, the guided search optimisation model is capable of improving GA to generate better solutions for affective design.

Publications Arising from the Thesis

Journal Article

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Nomenclatures

Attributes and variables

A_p	pth categorical attribute, where $p = \{1, 2, \cdots, P\}$
A_q	qth quantitative attribute, where $q = \{1, 2, \cdots, Q\}$
L_p	Number of items in the domain of pth categorical attribute
l	Data instance l, $l = 1, 2, \dots, n$
N	Number of product samples
n	Number of data instance
P	Number of categorical attributes
Q	Number of quantitative attributes
v_q^{lower}, v_q^{upper}	The lower and upper values of qth quantitative attribute
$x_{p,l}$	l th option in the domain of p th categorical attribute, $l = \{1, 2, \cdots, L_p\}$
y_l	The rating of customer affection of data instance l
z	Product sample z
ψ	The rule approximation of customer affection
$\psi^{lower}, \psi^{upper}$	The lower and upper approximations of customer affection
ψ_L	Level of customer affection in a rating scale
$\lvert\psi_L\rvert$	Number of levels of customer affection in a rating scale
ψ_{min}, ψ_{max}	The minimum and maximum levels of the rating scale
ψ_A	The aggregate decision made from a rule set
$\psi_A^{lower}, \psi_A^{upper}$	The lower and upper approximations of an aggregate decision made from rule sets
ψ_H	The rule approximation of ‘handiness’ of mobile phone design
ψ_{HA}	The aggregate decision made from a rule set for ‘handiness’ of mobile phone design

Genetic algorithms

a_p , a_q	The activation flags for pth categorical attribute and qth quantitative attribute, respectively
$\boldsymbol{c}_{1,d}$, $\boldsymbol{c}_{2,d}$	The values of new children for dth real number (crossover)
$\boldsymbol{c}_d$	The values of new child for dth real number (mutation)
N_{pop}	Number of individuals in the GA population
$\boldsymbol{p}_{1,d}$, $\boldsymbol{p}_{2,d}$	The values of parents for dth real number (crossover)
$\boldsymbol{p}_d$	The values of parent for dth real number (mutation)
X_p	The gene of pth categorical attribute
X_q	The gene of qth quantitative attribute
Y	The gene of decision attribute
ζ_d	The changing rate of arithmetic crossover
δ_d	The changing rate of polynomial mutation
η_c	Crossover distribution index
η_m	Mutation distribution index
$\lambda_d^{lower}, \lambda_d^{upper}$	The lower and upper bounds for polynomial mutation
ξ_d	The random number for arithmetic crossover

Rule-mining models

$CFw_{(R)}$	The confidence factor of a rule
$Conf(R)$	The confidence of rule *R*
$Acc(S)$	The accuracy of rule set *S*
$Cmplx(R)$	The complexity of rule *R*
$Cmplx(S)$	The complexity of rule set *S*
$Comp(S)$	The comprehensibility of rule set *S*
Def(*R*)	The definability of rule *R*
Def(*S*)	The definability of rule set *S*
$Int(R)$	The interestingness of rule *R*
M	Total number of the rules encoded in a chromosome of second stage of rule mining
Op	Relational operator, ≤ or ≥

R	An approximate rule
R_m	mth rule encoded in a chromosome of second stage of rule mining, where $m = \{1, 2, \cdots, M\}$
R_α	An activated rule that its weight is greater than τ
$R_{\alpha,L}$	A rule that is activated and contains the specific ψ_L
$\lvert R_{\alpha,L}\rvert$	Total number of $R_{\alpha,L}$ in the rule set
S	A rule set
$w_{(R)}$	The weight of rule R
$\lvert X\rvert$	Number of examples that satisfies rule antecedent X
$\lvert X \cup Y\rvert$	Number of examples that satisfies both antecedent X and consequence Y
$\Delta\psi$	The extent of a rule approximation
τ	User-defined threshold for rule selection

Dynamic neuro-fuzzy models

C'	The closest cluster to a data point
C_k	Cluster k, where $k = 1, 2, \dots, K$
c'	The centre of the closest cluster C'
c_k	The centre of cluster k
D_i	The distance between ith data instance and the corresponding cluster centre
D'	The distance between a data point and C'
D_{thr}	The threshold parameter of evolving clustering method (ECM)
f_k	kth TSK fuzzy model of a NF model
J	Number of input of a NF model
K	Number of cluster created by ECM
MF_{jk}	The membership function for fuzzification of jth input and kth fuzzy model
$N_{MF,j}$	Number of membership function for jth input
$\boldsymbol{P}$, $\boldsymbol{P}_u$	Inverse matrices for recursive least square (RLS)
r'	The radius of the closest cluster C'

r_k	The radius of cluster k
t	The period that a respondent participates in a longitudinal survey
u	Number of data instance for the initialisation of RLS
$X(n)$	The input vector of *n*th product sample
x_j	jth input of a NF model, where j = 1,2,…,J
x_j^i	The value of ith data instance for jth input of a NF model
$Y(t)$	Affective data set collected at time t
$y_n(t)$	Affective data towards *n*th product sample collected at time t
y	The output of a NF model
y_i	The value of ith data instance for training output of a NF model
Z_n	A new data instance presented to a dynamic NF model
α	Parameter of Gaussian membership function
$\boldsymbol{\beta}, \boldsymbol{\beta}_u$	Regression coefficient matrices of RLS
β_j	The regression coefficient of x_j
λ	Forgetting factor for RLS
μ	Parameter of Gaussian membership function
σ	Parameter of Gaussian membership function
ω_i	The weight of ith data instance

Design optimisation models

$Fit(\chi_i)$	The fitness value for the solution vector χ_i
N_{con}	Number of constraints formulated
N_{gs}	Number of guided search operators formulated
$N_{vio}(\chi_i)$	Number of constraints violated to solution vector χ_i
$Pen_{\mathrm{n}}(\chi_i)$	The penalty of nth constraint for the solution vector χ_i
$Pen_{sum}(\chi_i)$	The sum of penalties for the solution vector χ_i
R_{n}^-	The negative rule corresponding to nth constraint
v_q^{min}, v_q^{max}	The lower and upper limits of qth quantitative attribute for optimisation model
$y(\chi_i)$	The predicted customer affection for the solution vector χ_i based on the dynamic NF model

γ_q	The random number for guided search operator
ρ_c, ρ_m, ρ_{gs}	The probabilities of performing crossover, mutation and GS operation, respectively
$\chi_{\boldsymbol{c},\boldsymbol{g}}$	The child solution vector obtained based on gth GS operator
χ_c^{best}	The best child of the children obtained based on GS operators
χ_i	The solution vector of ith chromosome
χ_{Opt}	The solution vector containing the optimal attribute settings
$\chi_{\boldsymbol{p}}$	The solution vector of parent chromosome

Chapter 1 Introduction

Manufacturers currently face a highly competitive environment. Consumers are more demanding because of the more choices available in the market as well as globalisation. Design for performance and usability plays an important role in product development to gain a competitive edge. Products contend with functional differentiation by delivering superior functionality, performance, and reliability. However, product technology has proceeded to be more sophisticated and accessible, and this trend is gradually reducing the marginal value of adding new functions to a product. Today, customers consider functionality, ease-of-use, and reliability as part of product requirements, such that design for performance and design for usability can no longer guarantee a competitive advantage (Liu, 2003). Aside from these tangible product aspects, customers also consider intangible and emotional aspects, such as metaphors, novelty, personality, aesthetics, and style of products (Crilly *et al*., 2004; Demirbilek and Sener, 2003). Design attributes, such as form and colour, evoke the affective responses of customers to products. Products with good affective design can attract customers and influence their choices and preferences, such as loyalty and joy of use (Creusen and Schoormans, 2005; Noble and Kumar, 2008). The satisfaction of the emotional needs of the customers is synonymous with the ‘feeling quality’ of the products (Lai *et al*., 2005a). The affective design involves activities that identify, measure, analyse, and understand the relationship between the affective needs of the customer domain and the perceptual design attributes in the design domain. Moreover, affective design provides decision support for the design optimisation process, such that appealing products that satisfy the emotional needs of target customers can be developed successfully (Jiao *et al*., 2006; Khalid and Helander, 2004). Affective design is an important design strategy for customer-oriented and market-driven product development because it increases customer satisfaction and adds value to products. Affective design can be applied to various products, such as automobiles, furniture, cosmetic containers, and many other products used in daily life (Catalano, 2002; Nagamachi, 2002). Research in affective design can develop knowledge in design methodology, thereby developing more products that appeal to customers.

Understanding customer needs is important in product design. However, eliciting diversified consumer needs and translating these needs to product configuration effectively and promptly present a great challenge to manufacturers under short product life cycles in the industry. Companies commonly conduct market analyses to acquire customer needs. Quality function deployment (QFD) is commonly applied to translate the collected customer needs to technical requirements for new product development. However, these methods focus on acquiring conscious and explicit consumer needs only (Tarantino, 2008).

Different from explicit and tangible needs of functionality and usability, affective needs of customers imply implicit and subjective customer perception (Jiao *et al*., 2008). Even customers may not be able to realise and express their feelings and latent perception of a product. The affective responses of customers to a product vary greatly between individuals. This inconsistency leads to the difficulty in extracting the affective needs of customers. In the industry, affective design still heavily relies on the experience and intuition of designers. However, designers may not fully recognise the affective needs of customers because perceptual and cognitive gaps in design appreciation always exist between designers and customers (Crilly *et al*., 2004; Hsu *et al*., 2000). The emotional and implicit customer needs can be explored by conducting focus groups and in-depth interviews. However, the information collected from these methods is subjective and qualitative. This limitation opens the need to develop techniques and methodologies that investigate the affective aspects in product design in an objective and quantitative manner.

1.1 Research background

Owing to the importance of affective design, quite a few previous studies attempted to adopt QFD and robust design approaches to affective design (Chan and Wu, 2002; Lai *et al.*, 2005a). However, the approaches are incapable of dealing with the subjective aspect of affective design (Tarantino, 2008). Kansei engineering (KE) or affective engineering method was developed by Nagamachi (1995) to capture and transform customer affections of products into perceptual design attributes of affective design. KE provides a systematic approach that quantitatively surveys the affective meaning related to a product domain based on the semantic differential method (SD) (Osgood *et al*., 1971). For typical Kansei approaches, relationships between customer affection and design attributes are quantified using statistical methods, such as regression analysis, and quantification theory type I (Nagamachi, 1995; Nagamachi *et al*., 2008). KE has been applied in various product designs, such as car interiors (Jindo and Hirasago, 1997), drink bottles (Barnes and Lillford, 2009), and surface tactility of plastic products (Choi and Jun, 2007).

Consumer affections are usually ambiguous and result in inconsistency in the survey data and generally present a non-linear relationship with design attributes (Lai *et al*., 2005a). In view of the fuzzy and non-linear behaviour of the affective modelling, KE employing statistical methods based on the assumptions of simple linear relations and normal distributions may not be capable of modelling customer affections (Aktar Demirtas *et al*., 2009; Nagamachi *et al*., 2006; Park and Han, 2004; Zhai *et al*., 2009a). Recent studies of affective design attempted to apply computational intelligence techniques, such as association rule mining, artificial neural networks (ANN), fuzzy logic, and rough set theory, in dealing with the ambiguity of affective data and non-linearity of the affective modelling (Jiao *et al*., 2006; Hsiao and Huang, 2002; Lai *et al*., 2005b; Park and Han, 2004; Ma *et al*., 2007; Nagamachi *et al*., 2006; Zhai *et al*., 2009a). The studies can be classified into two types. One type of studies focuses on knowledge acquisition using rule-mining techniques, such as association rule mining and rough set theory (Jiao *et al*., 2006; Zhai *et al*., 2009a). The acquired design rules can help designers to have a better understanding of the relationship between customer affections and design attributes. However, based on the generated rules, optimal settings of design attributes for affective design cannot be determined. Another type of studies focuses on modelling affective relationships using model-based techniques, such as ANN, fuzzy logic and neuro-fuzzy network (Lai *et al*., 2005b; Park and Han, 2004; Ma *et al*., 2007; Hsiao and Tsai, 2005; Sun *et al*., 2000; Tsai *et al*., 2006). Unlike the rule-based approaches, model-based approaches can be used to develop prediction models through a training process. Both the rule-based and model-based approaches play important roles in supporting affective design. Although some computational intelligence techniques were attempted to support affective design, affective design is quite complex and has not yet been completely solved by existing approaches.

1.2 Research motivations

Affective design currently relies on designers' tactile knowledge accumulated from their experience very much. However, the approach is inadequate to deal with the challenges of a fast-changing competitive environment, increasing customer expectations and shortening product development time. Development of intelligent systems for supporting affective design using computational intelligence techniques is an effective means to improve quality and shorten the cycle time of affective design. The computational intelligence techniques, which employed in the previous studies of affective design, can be classified into model-based and rule-based. In general, model-based approaches involve development of mathematical models for predictive purposes, whereas rule-based approaches explore design knowledge using the 'IF-THEN' rules. Two types of approaches perform the acquisition of knowledge but differ in knowledge representation formalism. The former focuses on the generation of prediction models, whereas the latter centres on the readability and comprehensibility of semantic solutions to users. Each approach possesses its own advantages and limitations in managing knowledge of affective design. The models generated based on most of the existing model-based approaches are 'black-box' and it is difficult for designers to gain the understanding of affective design from them (Lai *et al*., 2005b; Yang and Shieh, 2010). However, if the knowledge regarding the relationships between customer affections and design attributes can be obtained, it would help designers to perform affective design effectively. Previous studies of developing intelligent systems for affective design are based on either rule-based approaches or model-based approaches. Research on investigating the use of both model-based and rule-based approaches in supporting affective design can be explored.

Since customer affections are changing with time, the capability of dynamic update of intelligent systems for affective design is important (Jiao *et al.*, 2008). Therefore, there is a need to study adaptive mechanisms of knowledge acquisition and modelling to address the dynamic issue.

1.3 Research aims and objectives

The research aims to investigate the application of computational intelligence techniques in the affective design of products. The objectives of the research are as follows:

- To generate approximate rules for affective design using a multi-objective genetic algorithm (MOGA) based rule-mining approach;
- To model the relationships between customer affections and design attributes of products using the dynamic neuro-fuzzy (NF) approach; and
- To develop an intelligent system for determining the optimal design attribute settings of affective design.

1.4 Organisation of the thesis

This thesis consists of seven chapters. The remaining chapters are outlined as follows:

Chapter 2 is a review of literature on affective design of products. The fundamental issues and well-known approaches related to affective design of products are reviewed. In addition, computational intelligence techniques used in previous research on affective design are re-examined. Some research gaps and opportunities are discussed.

Chapter 3 describes a proposed methodology for supporting the affective design of products from which an intelligent system can be developed.

Chapter 4 presents the design and development of the intelligent system, which consists of three models: a MOGA-based rule-mining model, a dynamic NF model, and a design optimisation model. The algorithm and detail design of each model are described.

Chapter 5 illustrates the implementation of the proposed intelligent system and a case study on mobile phone design. The results of each model are presented and discussed. The performances of the MOGA-based rule-mining model and the dynamic NF model are evaluated using cross-validation tests.

Chapter 6 discusses some assumptions and limitations of the present research, including the methodology, and intelligent system.

Chapter 7 concludes the research and gives some of the significant results. The major contributions of this research are described. Finally, some suggestions for future work are presented.

Chapter 2 Literature Review

This chapter reviews the related studies on the affective design of products. Section 2.1 outlines the fundamental issues on the affective design of products. Section 2.2 follows with a review of the conventional approaches for affective design. Section 2.3 offers an overview of intelligent systems and their applications in the analysis of the relationship between design and customer affection. Section 2.4 considers the issues and techniques for optimisation of product design. Finally, Section 2.5 summarises this chapter by discussing the research gaps and opportunities related to affective design.

2.1 Affective design

Affective design is the inclusion or representation of affect in the design process (Jiao *et al*., 2006). Affect refers to the emotional feelings or impressions of customers about a product (Lai *et al*., 2005a). Affective response describes the psychological response of a customer to the perceptual design attributes of a product (Demirbilek and Sener, 2003; Crilly *et al*., 2004). Design attributes (Chen *et al*., 2006; Barnes and Lillford, 2009) are synonymous to design characteristics (Nagamachi, 1995) or design elements (Jiao *et al*., 2006; Zhai *et al*., 2009a). Design attributes can be colour, material, size, shape, texture, and so forth. A product evokes certain affective responses from customers and users. The affective design of products develops a product that satisfies affective customer needs (Lai *et al*., 2005a). It also implies the activities to identify, measure, and analyse customer needs and affective responses for conceptual product design (Khalid and Helander, 2004). Jiao *et al*. (2006) asserted that affective design involves a mapping process from the affective needs of customer domain to the perceptual design attributes in the design domain, as shown in Figure 2.1. This figure illustrates how a designer achieves affective design and how the customer of the product will perceive and react. KE is a methodology commonly used in affective design. Section 2.2.1 provides a review of KE.

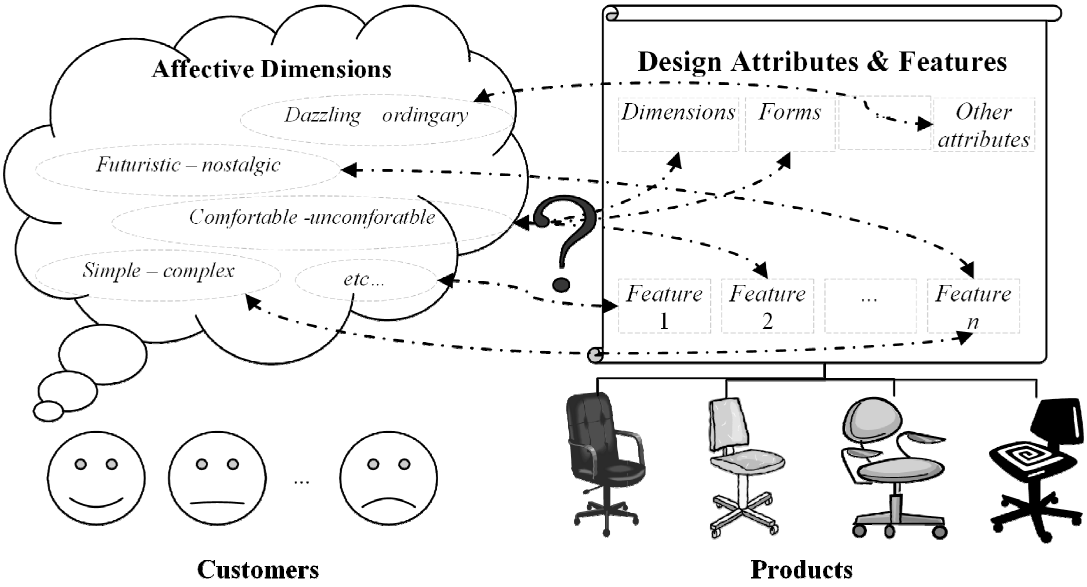


Figure 2.1 Mapping process in affective design

2.2 Conventional approaches to affective design

As mentioned above, KE is a well-recognised method for affective design. Section 2.2.1 reviews the related studies in KE. QFD and robust design are two other conventional approaches used in previous research. Sections 2.2.2 and 2.2.3 discuss these approaches, respectively.

2.2.1 Kansei engineering

Nagamachi (1995) proposed KE or affective engineering (Barnes and Lillford, 2009; Nagamachi, 2008), which is a product development methodology of acquiring and transforming customer affections into design attribute settings using quantitative methods. 'Kansei' is a Japanese word that means psychological feelings, sensations, and emotions (Nagamachi, 1995). The framework of KE encompasses four tasks (Barnes and Lillford, 2007, 2009; Nagamachi, 1995; Schütte and Eklund, 2005):

1. Definition of product domain
2. Determination of dimensions of customer affections
3. Determination of design attributes and attribute options
4. Evaluation of relations between customer affections and design attributes

Defining product domain refers to specifying the kinds of products to be studied. Different sets of words are used to describe customer affections in different product domains, and semantic meanings of words vary corresponding to the product category. For an effective KE experiment, products should contain a homogenous semantic structure. The term 'visual comfort' assesses the overall image regarding the aesthetic judgment of a product (Chang, 2008). However, a product can be associated with the multiple dimensions of customer affections. A set of semantic words is required to describe the various dimensions of customer affections in the product domain. The KE framework includes the processes of identifying the semantic words associated with a product domain and determining the most appropriate semantic words for representing the fundamental dimensions of the customer affections of the product. Two methods, qualitative and quantitative, can be used to determine the dimensions. Qualitative mapping techniques, such as affinity diagram and category classification methods, have been employed to identify the semantic hierarchical structure (Nagamachi, 1995, 2002, 2008; Schütte *et al*., 2004). Quantitative methods mainly involve multivariate statistical analyses, such as factor analysis, principal component analysis, and multidimensional scaling (Barone *et al*., 2009; Nagamachi *et al*., 2008). SD is a survey method that many KE studies use to measure customer affections towards products (Barnes and Lillford, 2009; Hsiao and Chen, 2006; Jiao *et al*., 2006; Khalid and Helander, 2004, 2006; Nagamachi, 2002). The SD scale of a five- or seven-point bipolar pair of affective words is used as the basis for the evaluation of the products (Osgood *et al*., 1971). Many previous studies on affective design also employ SD questionnaires to collect customer affections (Akay and Kurt, 2009; Chuang and Ma, 2001; Hsiao and Chen, 2006; Khalid and Helander, 2004; Kongprasert *et al*., 2008; Lin *et al*., 2007; Petiot and Yannou, 2004; Zhai *et al*., 2009a).

A number of KE studies apply morphological analysis to identify and categorise common design attributes of a product category (Chang, 2008; Chen and Chuang, 2008; Hsu *et al*., 2000; Nagamachi *et al*., 2008; Wang, 2009). Morphological analysis is a method for systematically structuring and exploiting the candidate solution based on a design table or ‘morphological matrix’. Design attributes and their options are fully listed in the design table. They are effective in generating new product concepts by reassembling the selected options of design attributes. A product commonly contains many design attributes. An analysis of the importance of design attributes may be required for attribute selection. The Pareto Diagram has been employed to select design attributes in the KE process (Barone *et al*., 2007; Lanzotti and Tarantino, 2008; Schütte *et al*., 2004).

KE aims to transform customer affections into design attribute settings. One important task of the KE framework is the evaluation of relationships between the defined affective dimensions and design attributes. Previous studies on KE apply various regression analyses, including quantification theory I, ordinal logistic regression, partial least square analysis, and exploratory analysis (Barone *et al*., 2007; Nagamachi *et al*., 2008; Nagamachi, 2002; Seva *et al*., 2007). Quantification theory type I is a variant of the multiple regression model, which KE studies commonly use (Bahn *et al*., 2009; Chang, 2008; Jindo *et al*., 1995; Lai *et al*., 2006; Nagamachi, 2002). This model employs multiple linear regression analysis with dummy variables that handle the explanatory variables with nominal values (Lanzotti and Tarantino, 2008; Tanaka, 1979). Another regression method that models the relationships in KE is multilevel regression or the hierarchical linear model (Seva *et al*., 2007). The multilevel regression computes intra-class correlation that improves the interpretability of affective data. As mentioned previously, multivariate statistical analyses, such as factor analysis and principal component analysis, help determine the affective dimensions. Nagamachi (2008) applied a partial least square regression in Kansei statistic analysis to better evaluate the data projected by the principal component analysis.

The major limitation of applying multiple linear regressions in the modelling of the relationships is that only linear regression models can be developed (Aktar Demirtas *et al*., 2009; Zhai *et al*., 2009a). Using an ordinal rating scale for the evaluation of products is common in a KE study. Linear regressions are inappropriate in analysing ordinal data. Barone *et al.* (2007) proposed a weighted ordinal logistic regression model and reported an improvement in fitting the affective data. Logistic regression is more suitable to deal with ordinal affective data and categorical design attributes than linear regression. The introduction of weights in the logistic regression model can improve the model fitting.

Previous studies on KE can be classified into two areas. The first area covers the determination of the dimensions of customer affections and semantic structures about product styles, images, or groups. The second area centres on the analysis of the relationships between customer affections and design attributes (Aktar Demirtas *et al.*, 2009). Statistical methods were commonly used in the previous studies on KE. Research on the first area commonly involves multivariate statistical methods, such as factor analysis and principal component analysis, whereas the second area commonly uses regression. Figure 2.2 shows the KE framework.

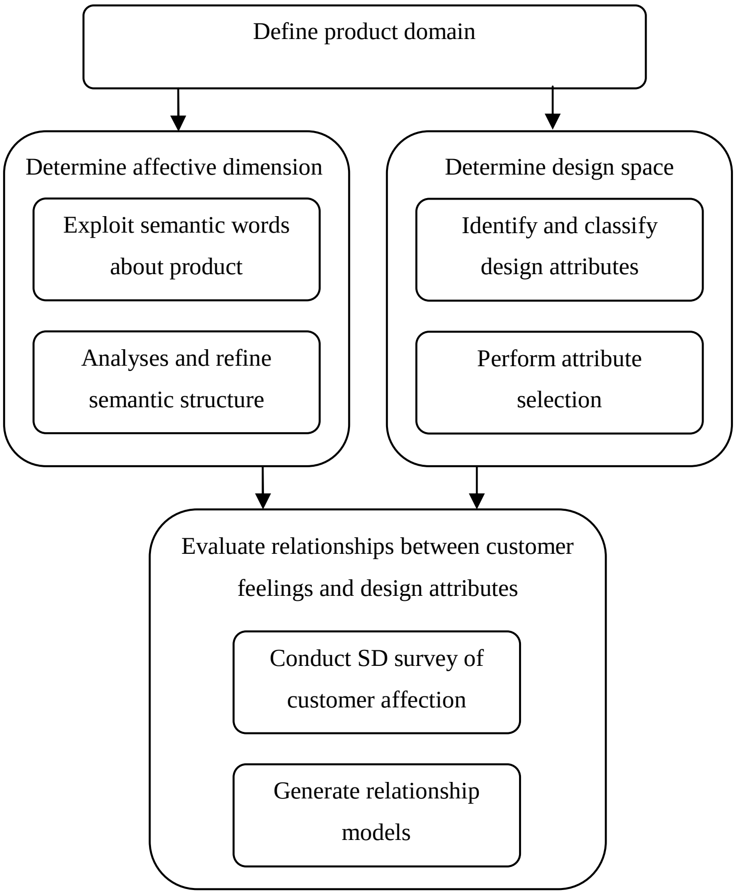

Define product domain
Determine affective dimension
Exploit semantic words about product
Analyses and refine semantic structure
Determine design space
Identify and classify design attributes
Perform attribute selection
Evaluate relationships between customer feelings and design attributes
Conduct SD survey of customer affection
Generate relationship models

Figure 2.2 Framework of Kansei engineering

2.2.2 Quality function deployment

Chan and Wu (2002) reported that the product planning of new products for enhancing product performance and customer satisfaction widely uses QFD, which aids to translate customer requirements to technical design requirements based on voice of customers. Previous studies on QFD discuss explicit consumer needs regarding tangible product aspects, such as functionality, performance, and reliability (Tarantino, 2008). However, the affective design of products is associated with intangible and implicit needs of customer affection towards product styles or images. Jin *et al.* (2009) proposed an extended QFD approach to consider product usability evaluation based on customer sensation. A sensibility evaluation is conducted to collect the rating of user sensation towards various design factors, such as form, harmony, and overall feeling of use. The approach prioritises design factors in a house of quality using the analytical hierarchy process (AHP) and correlation analysis, and then determines the models for relating user sensations and design factors using multiple regression analysis.

2.2.3 Robust design approach

Lai *et al.* (2005a) proposed a robust design approach for affective design based on the Taguchi method to determine the optimal setting of design attributes that can achieve a high ‘feeling quality’ of a product. The signal-to-noise (S/N) ratio is used to measure the effects of design attributes on the feeling discrepancy. The optimal settings of design attributes are determined based on the ‘small-is-better’ S/N ratio for the strongest ‘feeling quality’ of the product.

2.3 Computational intelligence for affective design

Computational intelligence techniques are used for data mining and modelling of complex problems and systems in engineering design (Saridakis and Dentsoras, 2008). In recent years, the research on affective design employs various computational intelligence techniques, such as association rules, rough sets, fuzzy logic, grey theory, ANN, and support vector machines (SVM). Compared with statistical techniques, computational intelligence techniques are normally more capable of handling the ambiguity of affective data and the nonlinear relationships between customer affections and design attributes. The evaluation of products relies on SD scales of 1 to 5, 1 to 7, and 1 to 9 to measure customer affection. The compiled data are ordinal, and thus the statistical linear regression used in the previous studies of affective design is inadequate in dealing with the categorical or ordinal data (Aktar Demirtas *et al*., 2009). Barone *et al.* (2007) proposed an ordinal logistic regression model for modelling such affective relationships. Although the logistic regression model is more suitable for evaluating categorical design attributes, this method is limited to the use of only two levels of attributes in the experiments. In addition, statistical-based models typically formulate design attributes as individual variables. Correlation or interaction effects among design attributes cannot be properly addressed (Aktar Demirtas *et al*., 2009).

Some recent studies introduce computational intelligence into the affective design to overcome the limitations of the statistical methods as mentioned previously. The studies can be classified into two categories: rule-based and model-based. As regards readability and comprehensibility of semantic solutions to users, rule-mining techniques generate the decision rules, which are in the form of ‘IF-THEN’ statements and provide good semantic representation. Association rule and rough-set mining techniques have been employed to generate rules for affective design of products. Sections 2.3.1 and 2.3.2 review the related studies on the two types of data mining techniques, respectively. Unlike rule-based approaches, model-based approaches develop models for relating inputs and outputs. The models may or may not have semantic representation. Sections 2.3.3 to 2.3.8 review the previous studies on the application of model-based computational intelligence techniques in affective design.

2.3.1 Association rule mining

Association rule is one of the popular techniques in data mining. Jiao *et al.* (2005; 2006) proposed a data-mining system to identify affective mapping patterns based on association rules. The system performs the mapping between the dimensions of customer affections and design attributes, and expresses the discovered knowledge in association rules, i.e., ‘affection dimension $X \Rightarrow$ design attributes Y’. The association rule mining is a process of searching frequent item-sets as rules from a large database, which contains the data sets of customer affections and design profiles. As the data mining process uses raw data, it avoids data loss caused by using average values in the conventional Kansei statistical analyses (Aktar Demirtas *et al.*, 2009). Jiao *et al.* (2008) applied the association rule mining in analysing affective design with ambient intelligence and the developed system can facilitate the interactive decision-making of affective design.

‘Support’ and ‘confidence’ are two criteria widely used in data mining. Support is a measure of the frequency of a pattern recorded in the entire database, whereas, confidence is a measure of the strength of an item X (rule condition) inducing another item Y (rule consequent). User-defined thresholds of support and confidence are required to screen out the rules with poor quality in the conventional data-mining techniques. The challenge of determining the optimal values of these thresholds has been discussed in previous studies (Jiao and Zhang, 2005; Jiao *et al*., 2006; Mitra *et al*., 2002; Yang *et al*., 2008). Jiao *et al.* (2006) introduced a goodness index as the rule criterion for mining design rules instead of the thresholds of support and confidence. The goodness index provides a measure of rule accuracy by comparing the expected affective rating with the rating achieved by the discovered rules. Yang *et al.* (2008) proposed a modified goodness index with the use of normalised ratings. One limitation of this approach is its inadequacy in accounting for levels of customer affection with crisp values.

2.3.2 Rough set-based rule mining

Owing to the ambiguity of customer affections, the rough set theory proposed by Pawlak (1991) has been adopted in affective design of products. The basic concept of the rough set theory is to formulate an approximation of a crisp set from vague or imprecise information. A rough set consists of a pair of lower and upper approximations of the data set. The lower approximation set is a subset of members that are certainly classified as elements of the target class. The upper approximation set is a vague approximation that covers the possible members of the target set. When there is difference between the lower and upper approximations, the boundary region is non-definable and the members cannot be certainly classified into a class. Rough sets provide an effective approximate reasoning for vagueness and uncertainty of a data set. Nagamachi *et al.* (2006) advocated that the rough set theory could be used for KE because the rough set theory is suitable for dealing with ambiguous and uncertain data.

A rough set-based rule-mining process extracts ‘IF-THEN’ rules by finding the minimal subset of attributes that induce the most consistent decision (Mitra *et al*., 2002). Okamoto *et al.* (2007) compared the rough set approach with the statistical regression approach in KE, and concluded that the rough set approach is more reliable in generating more specific design rules when interaction exists between design attributes (predictive variables). Nishino *et al.* (2006) introduced the rough set-based rule-mining method based on the variable precision Bayesian rough sets (VPBRS) theory into KE. The VPBRS approach combines the rough set and Bayesian probability theories to extract approximate rules with probabilistic reasoning (Ślęzak and Ziarko, 2003). Zhou *et al.* (2009) employed a rough set-based *K*-optimal rule discovery method in mining rules that perform the mapping between design attributes and multiple dimensions of customer affections. The *K*-optimal rule discovery method was applied to extract the most important rules according to the rule importance measure, which is based on the rough set theory. Shi *et al*. (2012) applied rough set theory and association rule-mining techniques on developing a Kansei knowledge extraction system. The system primarily extracts key attributes from data sets using rough set theory and then generates rules using Apriori algorithm. Apriori algorithm is a classic association rule-mining algorithm. It formulates rules by joining additional attributes to the key attributes and select effective rules based on support and confidence thresholds. The proposed approach was found better than conventional Kansei approaches in data reduction with lower feature loss. However, these approaches are limited to dealing with customer affections in a binary classification (e.g., ‘beauty or not’, and ‘luxurious or not’) and are incapable of measuring the strength of customer affections.

To acquire the ambiguous customer affections of products, customer evaluation questionnaires use multi-level rating scales, such as the Likert and SD scales. As mentioned in Section 2.2.1, ratings obtained from the surveys are ordinal data. As a result, consideration of the ordinal properties of customer affections is important to process the affective data. Zhai *et al.* (2009a, 2009b) employed the dominance-based rough set (DRS) theory in affective rule mining because it can generate the approximation of a set of ordinal data. Generally, DRS determines the approximations of attributes with preference-ordered domains based on an outranking relationship (Greco *et al.*, 2002, 1999). The DRS approach formulates rough approximations of unions of preference-ordered decision classes called upward and downward unions. Moreover, the DRS approach can induce decision rules from the boundary regions of the upward and downward unions according to outranking relationships. Compared with the conventional rule-mining approaches, the DRS approach is more suitable for rule mining for affective design, as most rule-mining approaches for affective design are limited to handling discrete classes. However, DRS requires a conversion of design attributes from nominal to ordinal according to category scores of attribute items (Zhai *et al.*, 2009a, 2009b). The category score is simply an average value of evaluation ratings of design, including the particular item. The order of attribute options may not be sorted properly because design attributes usually do not possess an explicit preference order. The category score method is inadequate in dealing with interactions among attributes. Although the rough set approach can cope with the ambiguous survey data for affective design using approximations, it is limited to the application on categorical attributes only and cannot be used to deal with the rule-mining problems that involve quantitative attributes without data discretisation. The discretisation process may cause loss of information in data sets. In addition, defining optimal intervals to transfer a continuous attribute is difficult.

2.3.3 Grey theory

Grey theory is a technique used to model uncertain and incomplete information (Deng, 1982). Grey theory defines situations with certain and fully known information as white and those with no information as black. Grey information is the uncertain and incomplete information that belongs to neither white nor black states.

Hsiao and Liu (2002) applied shape morphing and grey prediction GM(1,1) model to study the relationships between design attributes and customer affections. They proposed an improved grey prediction model using the Fourier series residual correction. The grey prediction model integrates with a computer-aided design system for the automatic design of the product form for a computer monitor design study (Hsiao and Liu, 2002). However, GM(1,1) models can only handle a single attribute and a first-order grey model (Lai *et al*., 2005b). A grey prediction GM(1, *n*) model has also been applied to show the relationship between customer affection and *n* design attributes (Lai *et al*., 2005b). The model can handle uncertain and incomplete information effectively with very few data sets (Deng, 1982). The grey prediction technique is found suitable for affective design when the number of experimental data sets is small (Lai *et al*. 2005b).

2.3.4 Artificial neural network

ANN is a non-linear mapping mechanism inspired by the biological neural network of human beings or other creatures (Priddy and Keller, 2005). The network consists of simple processing units called neurons, which operate in parallel. A large number of neurons link to construct the ANN through weighted connections. An ANN can be trained to solve specific problems, such as pattern recognition and data classification, through a learning process by adjusting the values of the weights of connections among the neurons. Back-propagation (BP) is the most popular supervised learning method for training multilayer neural networks (MLNN). BP adjusts the interconnection weights to map the input and output patterns in the training process using an error convergence technique, such as gradient descent algorithms. A trained network produces the desired output based on the corresponding input patterns.

ANN has been applied in affective design because of their learning power on the nonlinear properties. The MLNN model the nonlinear relationships between design attributes and customer affections for the designs of office chairs (Hsiao and Huang, 2002), mobile phones (Lai *et al.*, 2005b), and form-colour matching (Lai *et al.*, 2006; Lin *et al.*, 2008). Generally, the architecture of an MLNN model consists of a three-layered structure, including input layer, hidden layer, and output layer, as shown in Figure 2.3. BP is employed for the training of the MLNN models. After the training, the models can predict the perceptual values of new design attribute settings. Chen *et al.* (2003) adopted the radial basis function neural network (RBFNN) as an alternative ANN to evaluate the multicultural factors for product design and development. The radial basis functions of the RBFNN are capable of representing a bell-shaped distribution, and the RBFNN can model fuzzy relations similar to fuzzy inference systems (Jang and Sun, 1993). Therefore, RBFNNs are quite suitable for modelling the relationships in affect design, which normally involves a high degree of fuzziness. Chen *et al.* (2006) proposed a prototype system to model the relationships between design attributes and customer affections using a hierarchal analysis, as well as a Kohonen self-organising map (SOM) neural network. The process requires less training data of SOM neural networks because they perform unsupervised learning based on a nonlinear clustering. The main advantage of the ANN is the development of models through learning from data without requiring prior knowledge. Although a trained ANN possibly can provide an accurate prediction or classification, it is known as a 'black box' model from which meaningful knowledge is very difficult to extract (Lai *et al.*, 2005b; Yang and Shieh, 2010).

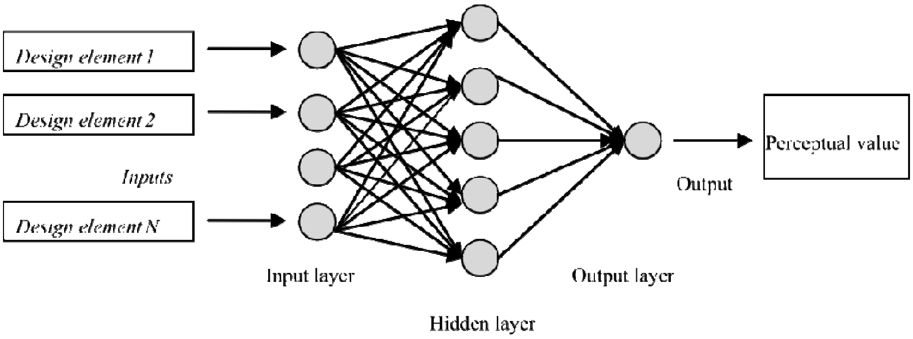


Figure 2.3 Architecture of an ANN for affective design

2.3.5 Fuzzy logic

Fuzzy logic can deal with vague data similar to the rough set theory. Fuzzy logic is a technique for reasoning fuzzy issues in the real world in matters of degree instead of crisp matters. This technique enables the expression of concepts, especially linguistic terms, as a degree of truth between 0 and 1 using fuzzy memberships, such as triangular and trapezoidal memberships. Fuzzy logic has been applied in affective design because customer affections of products are fuzzy and uncertain. In other words, the aesthetic judgment of a product depends on the degree of customer preference. Lin *et al.* (2007) proposed a fuzzy rule-based approach with a degree of support for the rule weighting in a case study on mobile phone design. The fuzzy rule-based approach is a comprehensible Mandeni-type fuzzy model that enables users to define the values of both design attributes (predictive variables) and ratings of customer affection (decision attribute) as simple fuzzy memberships. However, this approach requires the prior knowledge of experts to define the parameter settings of the fuzzy MFs.

Park and Han (2004) proposed a Takagi-Sugeno-Kang (TSK) fuzzy rule-based approach for affective design. Their proposed approach consists of two processes, namely, the subtractive clustering for the determination of the parameters of fuzzy membership functions (MFs) of input spaces and the least-squares estimation for the generation of local linear models. The parameter settings of fuzzy MFs of the TSK model are obtained from the results of clustering analysis. This method helps reduce errors compared with the conventional methods in which the parameter settings. The sample data are grouped according to the similarity of design attributes (input space). A fuzzy rule is formulated as a local model for each cluster in the fuzzy rule-based model. The rule represents the specific affective relationship of the corresponding cluster of product samples. Generally, TSK models provide more accurate predictions than Mandeni models because TSK models formulate a first-order linear model for each rule consequent rule and produce a precise numerical output. The results of their work demonstrate that the prediction performance based on TSK fuzzy rule-based models is better than that of the conventional regression models (Park and Han, 2004).

2.3.6 Fuzzy analytic hierarchy process

AHP is a technique for multi-criteria decision making by organising criteria and alternative solutions in a hierarchical structure (Saaty, 1990). To solve a complex decision problem, the AHP decomposes the decision problem into a hierarchy of measurable criteria that can be analysed independently. Pairwise comparisons of alternative solutions are performed to evaluate the priorities (weights) against each of the criteria. Conventional AHP is unable to consider fuzziness in the decision-making process. By integrating the fuzzy set theory with AHP, the fuzzy analytic hierarchy process (FAHP) can represent the priorities and ratings of alternatives against the criteria using fuzzy memberships in the pairwise comparison matrix. Ma *et al.* (2007) the FAHP model to calculate fuzzy priorities of colour choices and yields the favourite choice from the alternatives. The introduction of the FAHP supports the decision-making of product colour selection (Ma *et al.*, 2007).

2.3.7 Hybrid artificial neural network and fuzzy logic approaches

The hybrid approaches of fuzzy logic and ANN combine the capability of fuzzy logic in the linguistic representation of knowledge and the adaptive learning capability of ANN for automatic generation and optimisation of a fuzzy inference system. The hybrid approaches have been attempted in affective design of products. Fuzzy neural networks have been introduced to establish the relationships between design attributes and consumer affections (Hsiao and Tsai, 2005; Sun *et al.*, 2000; Tsai *et al.*, 2006). The fuzzy neural network utilises a series of output nodes of the ANN to emulate a fuzzy membership grade of affection intensity and then determines the aggregate value of customer affection through defuzzification. Another NF model called neuro-fuzzy classification (NEFCLASS) has also been attempted to extract ‘IF THEN’ rules for classifying a product design into either ‘High’ or ‘Low’ satisfaction (Akay and Kurt, 2009). The main feature of NEFCLASS is in its embedded rule pruning mechanism, which can construct accurate and comprehensible classification rules. The Adaptive Neuro-Fuzzy Inference System (ANFIS) has been applied to generate nonlinear customer satisfaction models based on market survey data for new product designs (Kwong *et al*., 2009). The complex network structure of an ANFIS-based model can possibly be decoded into a set of fuzzy rules (Jang, 1993). Kwong *et al.* (2009) proposed a rule-refining method to extract the significant fuzzy rules from the trained ANFIS-based model by determining the active range of input membership values. The ANFIS usually represents a global model with a fully connected network. Although this design enables covering a whole range of input space, redundant rules accompany a surplus of node connections in the ANFIS-based model. ANFIS-based models usually suffer from high-dimensional problems because the number of fuzzy rules increases exponentially with the number of variables.

2.3.8 Support vector machine

SVM are a relatively new machine learning technique for the nonlinearly mapping of high-dimensional data (Cortes and Vapnik, 1995; Vapnik *et al*., 1996). SVM can be applied for classification and regression in a specific problem domain (Gunn, 1998), especially pattern recognition (Byun and Lee, 2002). The basic idea of the SVM is to isolate the cases in different classes by constructing a linear separating hyperplane with a maximum margin. For nonlinear problems, the SVM performs a transformation of data based on kernel functions, such as polynomials and radial basic functions. By applying kernel techniques, a nonlinear input space is transformed to a high-dimensional feature space that may be solved by the linear classifier of the SVM.

Shieh and Yang (2008) employed a fuzzy multi-class SVM to classify design attribute settings into dimensions of customer affections. The SVM applies a Gaussian kernel as a fuzzy MF to deal with the nonlinear correlation among the design attributes. The fuzzy multi-class SVM-based classifier comprises a set of one-versus-one fuzzy SVMs for the pairwise classification and a voting mechanism for the multi-class decision making. The limitation of the fuzzy SVM model is that it requires a time-consuming cross-validation process to determine the optimal parameter setting of the Gaussian kernel. Yang and Shieh (2010) applied support vector regression (SVR) to model the affective relationships for product form design. The optimal parameter setting of the SVR model is determined using a real-coded genetic algorithm (GA). The SVR model has been shown to provide better predictive performance than the BP neural network model.

2.4 Optimisation for affective design

One of the main tasks of performing affective design is to determine the optimal settings of design attributes for affective aspects of products to achieve maximum customer satisfaction. If the optimisation focuses on investigating the design utility for a particular customer affection or product image, then the problem is a single-objective optimisation problem. The problem can be extended to a multi-objective optimisation problem if several dimensions of customer affection require to be studied simultaneously. Various optimisation techniques, such as linear programming and nonlinear programming algorithms, GA, and simulated annealing, determine the optimal design attribute settings for the product family design (Simpso, 2004). Some of the optimisation techniques have also been employed in affective design (Chen and Ko, 2009; Hong *et al*., 2008; Hsiao and Liu, 2004; Yang and Shieh, 2010).

As mentioned in Section 2.2, Kansei statistical analyses were widely used in affective design. Various statistical regression methods have been applied to modelling the relationships between customer affections and design attributes. Aktar Demirtas *et al.* (2009) adopted a statistical regression method for modelling the relationship. Linear programming and nonlinear programming algorithms are applied to solve the optimisation model developed based the regression approach and obtain the optimal design attribute settings.

An alternative approach for design optimisation is based on heuristic algorithms, such as GAs and simulated annealing. GA is a stochastic and effective optimisation technique to search for near-optimal solutions for various problems of engineering design (Saridakis and Dentsoras, 2008). GAs have been applied in various areas of product design, such as product portfolio planning (Jiao *et al*., 2007), interactive generative design (Kim and Cho, 2000; Yanagisawa and Fukuda, 2005), and optimisation of affective design (Hsiao and Liu, 2004; Hsiao and Tsai, 2005; Jiao *et al*., 2008; Yang and Shieh, 2010). There are two main reasons why GAs are suitable for solving optimisation problems for affective design (Jiao *et al*., 2008). First, discrete variables are commonly used in affective design. Compared with traditional optimisation techniques, GAs perform better in solving combinatorial optimisation problems that involve discrete attributes (Jiao *et al*., 2007). Second, the optimisation problems of affective design are different from many problems of engineering design in which optimal solutions exist. A real optimal solution is difficult to obtain in affective design. Outliers commonly exist in survey data, and information is little at the conceptual design stage. Existing methods for affective design have difficulty in developing a highly accurate optimisation model, and they are limited to provide only an approximation of the relationships between customer affection and design elements. Although GAs are limited to yield near-optimal solutions, they are effective in obtaining the best solution under the circumstances. Moreover, GAs offer greater compatibility with different models, whether they are statistical, rule-based, or 'black-box' models (Saridakis and Dentsoras, 2008).

2.5 Concluding Remarks

This chapter reviews the previous studies on conventional and computational intelligence approaches as well as the literature on the optimisation for affective design. Some observations from the literature review are as follows.

First, previous studies in affective design attempted to use both rule-based and model-based approaches. Rule-based and model-based approaches have their own strengths and weaknesses in knowledge representation and modelling the relationships between customer affection and design attributes. However, no previous studies were found regarding the combination of rule-based and model-based approaches to affective design, such that the strengths of the two approaches could be of best use in performing affective design.

Second, the rules generated by rule-mining approaches can help designers easily understand the relationships between customer affection and design attributes. The rule mining for affective design has two main kinds of approaches, i.e., binary and multi-level classifications. The binary classification approach investigates whether a design attribute setting belongs to an affective dimension or not (Jiao *et al.* 2005; Nagamachi *et al.*, 2006; Akay and Kurt, 2009). The multi-level classification approach considers the levels of customer affections, which are surveyed using five- or seven- point rating scales. Multi-level classification rules can provide more information about affective design compared with the binary classification rules. Considering the ambiguity of survey data, the DRS-based rule mining generates approximate rules and better considers the interaction of multi-level problems for affective design (Zhai *et al.*, 2009a, 2009b). However, the rule-mining approaches mentioned above mainly generate rules for the classification of affective design, and they cannot well support the optimisation of affective design. In the design optimisation process, designers are interested in rules that can indicate the kinds of design attributes, values, and patterns that are both desirable and undesirable for maximising customer affection. However, previous studies do not consider interestingness of rules for affective design. Moreover, both the categorical and quantitative attributes are commonly used in affective design. Most rule-mining approaches in previous studies are limited to dealing with categorical attributes, and they cannot handle the quantitative attributes with continuous values.

Third, the hybrid approaches of fuzzy logic and ANN are capable of modelling affective relationships. NF models can deal with the fuzziness of affective and design data sets and can model the relationships between customer affections and design attributes from the data sets. ANFIS is a popular NF model used in previous studies on affective design. However, ANFIS cannot effectively handle problems that involve a number of attributes and fuzzy MFs (Kasabov, 2007a). As ANFIS forms a fully structured network to represent a global model, the ANFIS structure consists of numerous redundant hidden nodes. To model the affective relationships, a large number of fuzzy MFs may be involved in the formulation of an ANFIS-based model because one MF is required to represent each option of categorical attributes. Thus, the structure of the ANFIS-based models becomes very complex. This complexity may lead to a very long computation time for training the model or even failure of the training.

Forth, the optimisation problem of affective design is a combinatorial optimisation problem in which each design of products can be expressed as an attribute setting. GA has been adopted as an effective technique to search for a near-optimal attribute setting from various combinations of attribute options in the previous studies of affective design. Moreover, the objective functions of the optimisation problems for affective design generally are non-linear. This feature makes the optimisation problems of affective design different from other optimisation problems which underly parametric and explicit mathematical models. Regarding a combinatorial problem of maximising customer satisfaction, searching for an optimal attribute setting based on arbitrary combination may generate an impossible or undesirable design solution (Krishnan and Ulrich, 2001). Previous studies optimise attribute settings using typical GAs that are difficult to prevent arbitrary combination, and it is necessary to develop a better optimisation approach for affective design.

Chapter 3 Research Methodology

In this research, the proposed methodology for affective design mainly involves the processes of market survey, rule mining, affective relationship modelling, and design optimisation. Figure 3.2 shows the proposed methodology for the affective design.

In the proposed methodology, a specific type of products needs to be defined first, and samples of the defined product category should be collected. Common design attributes are then identified from the collected product samples. Design attributes commonly involve categorical and quantitative types. The ranges of quantitative attributes can be obtained by measuring the collected samples or as defined by users. For categorical attributes, morphological analysis is adopted to create a design table by emulating the possible options of attributes. For instance, the shape of a product feature can be round, square, rectangle, etc. A new design can be generated by combining the options of different design attributes.

Acquiring customer affections towards product design requires a market survey. In the survey, survey respondents are required to look at the graphics of product aesthetics and then rate their customer affection towards the affective design of the product samples. The SD method (Osgood *et al.*, 1971) is adopted to measure customer affections towards products. The SD scale can be a five- or seven-point scale with a pair of affective words. Figure 3.1 shows a template of survey questionnaires for affective design using a SD scale.

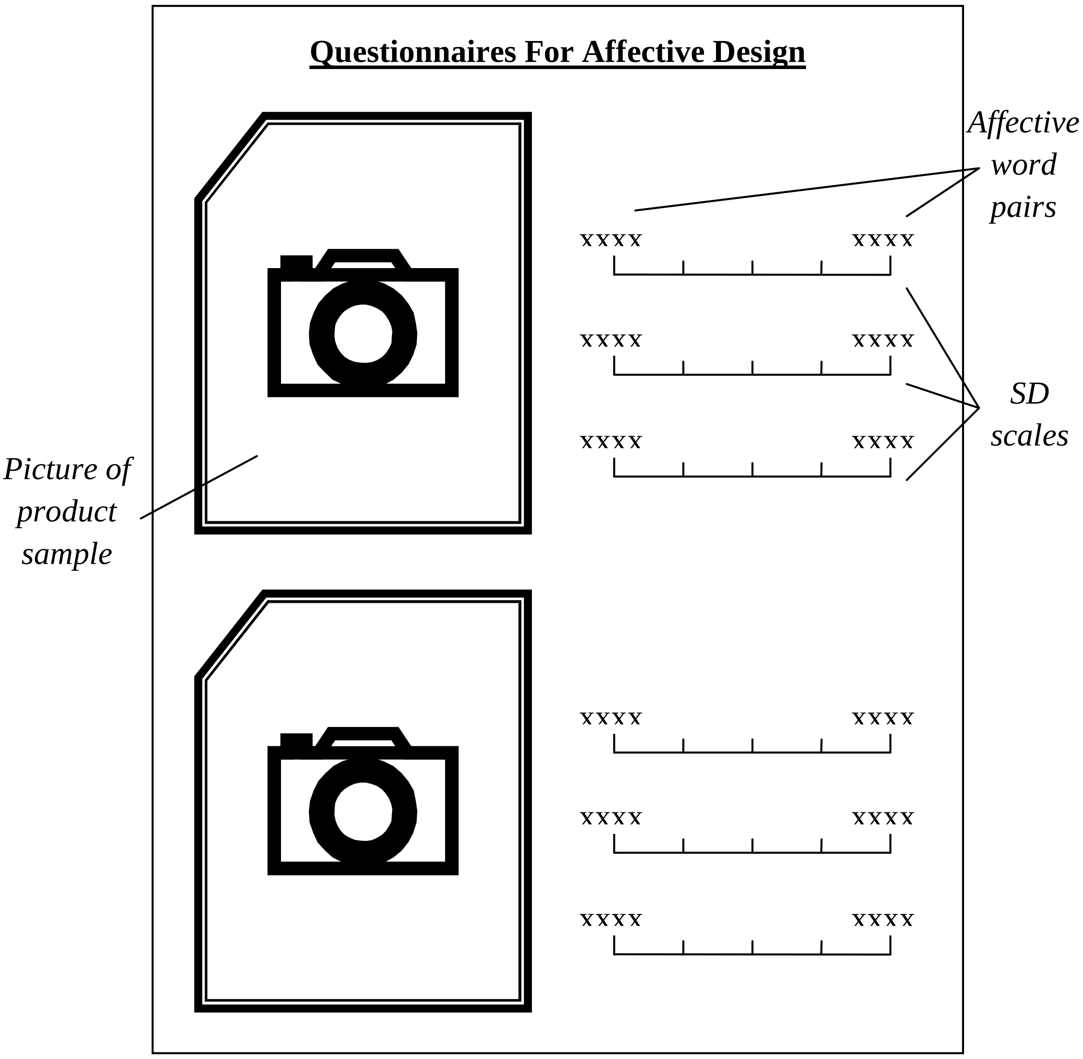

Questionnaires For Affective Design
Affective word pairs
xxxx
xxxx
SD scales
Picture of product sample

Figure 3.1 A template of questionnaires for affective design

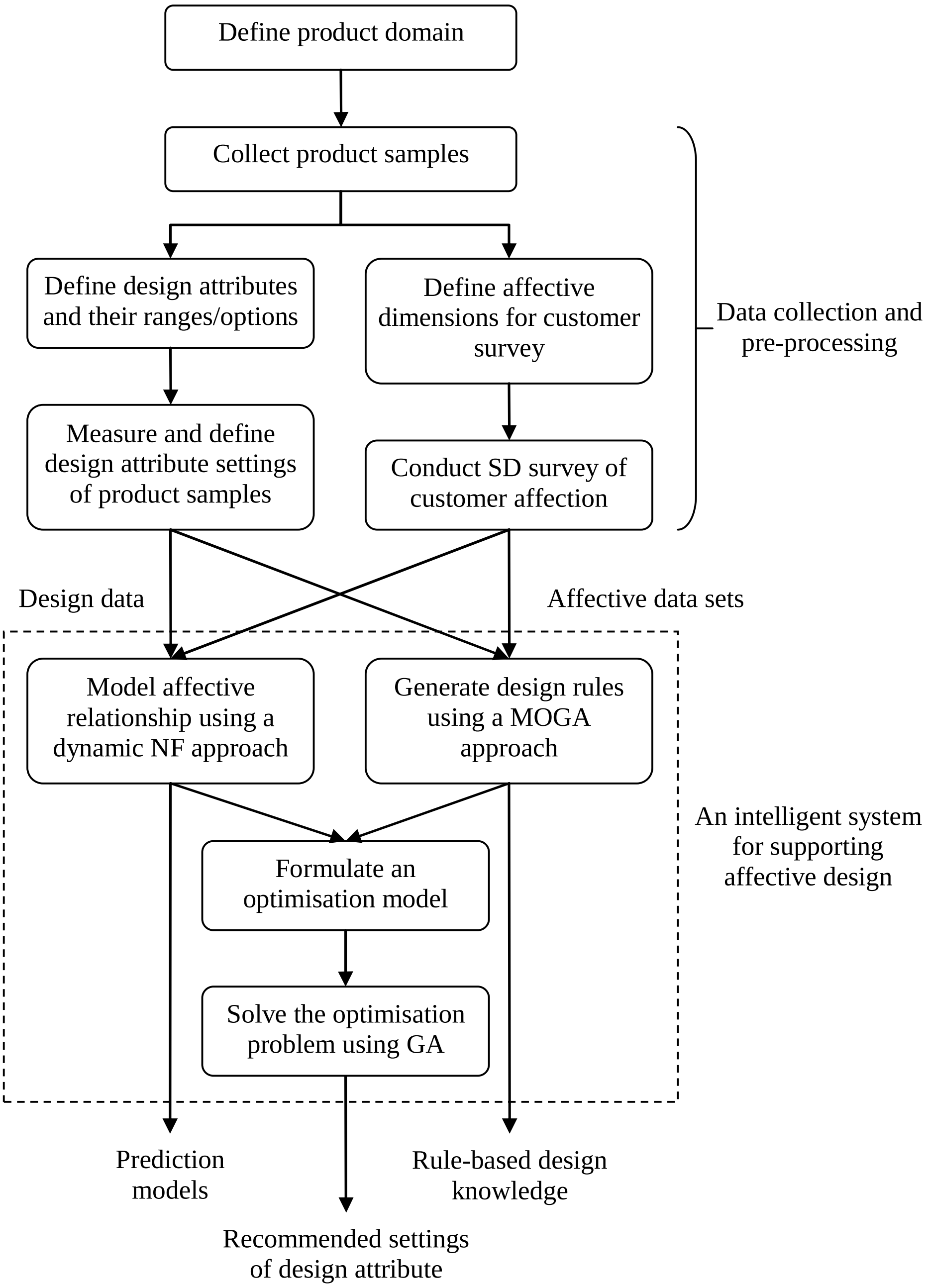

Define product domain
Collect product samples
Define design attributes and their ranges/options
Define affective dimensions for customer survey
Data collection and pre-processing
Measure and define design attribute settings of product samples
Conduct SD survey of customer affection
Design data
Affective data sets
Model affective relationship using a dynamic NF approach
Generate design rules using a MOGA approach
An intelligent system for supporting affective design
Formulate an optimisation model
Solve the optimisation problem using GA
Prediction models
Rule-based design knowledge
Recommended settings of design attribute

Figure 3.2 Proposed methodology for affective design of products

On the other hand, the design attributes to be studied need to be defined and the settings of the design attributes of the product samples are measured and recorded. Then, the measured data and survey data are used in the process of modelling affective relationships. Since the relationships between customer affections and design attributes are ambiguous, and highly non-linear, neural-fuzzy (NF) approach is introduced to modelling the relationships because it has good capability of handling ambiguous data, modelling non-linear systems, and linguistic representation of knowledge. However, there is a shortcoming of NF models. Typical NF models, such as ANFIS, are incapable of handling the problems which involve a large number of attributes. In this study, a dynamic NF approach is introduced to modelling the affective relationships. The NF models generated based on the approach are less complex and able to deal with a large number of design attributes. The algorithm of the dynamic NF approach is described in Section 4.3.

Both the measured data and survey data are also used in the process of rule mining. The purpose of the rule mining is to acquire design knowledge from data sets in order to provide designers with a better understanding of the relationships between customer affections and design attributes. Acquired design knowledge is expressed in 'IF-THEN' rules which are comprehensible and prescriptive. The rules can act as guidelines for designers to determine appropriate design attribute settings for affective design (Saridakis and Dentsoras, 2008). In contrast to the association rule and rough set mining used in the previous studies of affective design, the rule-mining approach proposed in this research considers the rule-mining problem as a rule optimisation problem. A MOGA-based rule-mining model is proposed to find the best rule set that represents knowledge of an affective design problem. The proposed rule-mining approach enables more rule criteria to be considered in the rule optimisation. The approach is also flexible to handle different types of attributes and able to overcome the weakness of association rule and rough set mining approaches in dealing with numerical attributes. MOGA is adopted to perform robust rule mining and appropriate rules is introduced to the rule-mining model to better deal with ambiguous and nonlinear affective relationships. The design of the MOGA-based rule-mining model is described in Section 4.2.

After the modelling of affective relationships and the rule-mining process, the generated NF models and rules can be used to formulate a design optimisation model. The design optimisation process is aimed to determine the optimal design attribute settings of products for maximising customer affective satisfaction. A guided search GA-based design optimisation approach is proposed in this study which employs a dynamic NF model (model-based) and appropriate rules (rule-based) for reasoning and solving the design optimisation problem. GA has good compatibility with different models regardless of rule-based or model-based (Saridakis and Dentsoras, 2008). It is also effective and reliable for solving combinatorial optimisation problems (Jiao *et al*., 2007). Figure 3.3 shows the processes of formulating the design optimisation model. Details of the design optimisation model are described in Section 4.4.

Before conducting the design optimisation, validation of the trained dynamic NF models and the generated design rules need to be performed. The dynamic NF model selected for formulating the optimisation model is required to have minimum errors and a good generalisation. Rule validation is also important to avoid using conflicting rules in defining constraints and search guides. Designers can evaluate, and refine the rule sets using their expert knowledge. After the model and rule validations, the chromosome encoding, objective function, constraints, search guides and parameter settings of GA are determined and the optimisation model can be formulated. The model needs to be verified by evaluating of the GA convergence results. After the verification, the optimisation problem is solved by the GA and optimal settings of design attributes for affective design can be determined. The details of the design and development of the system are described in Chapter 4.

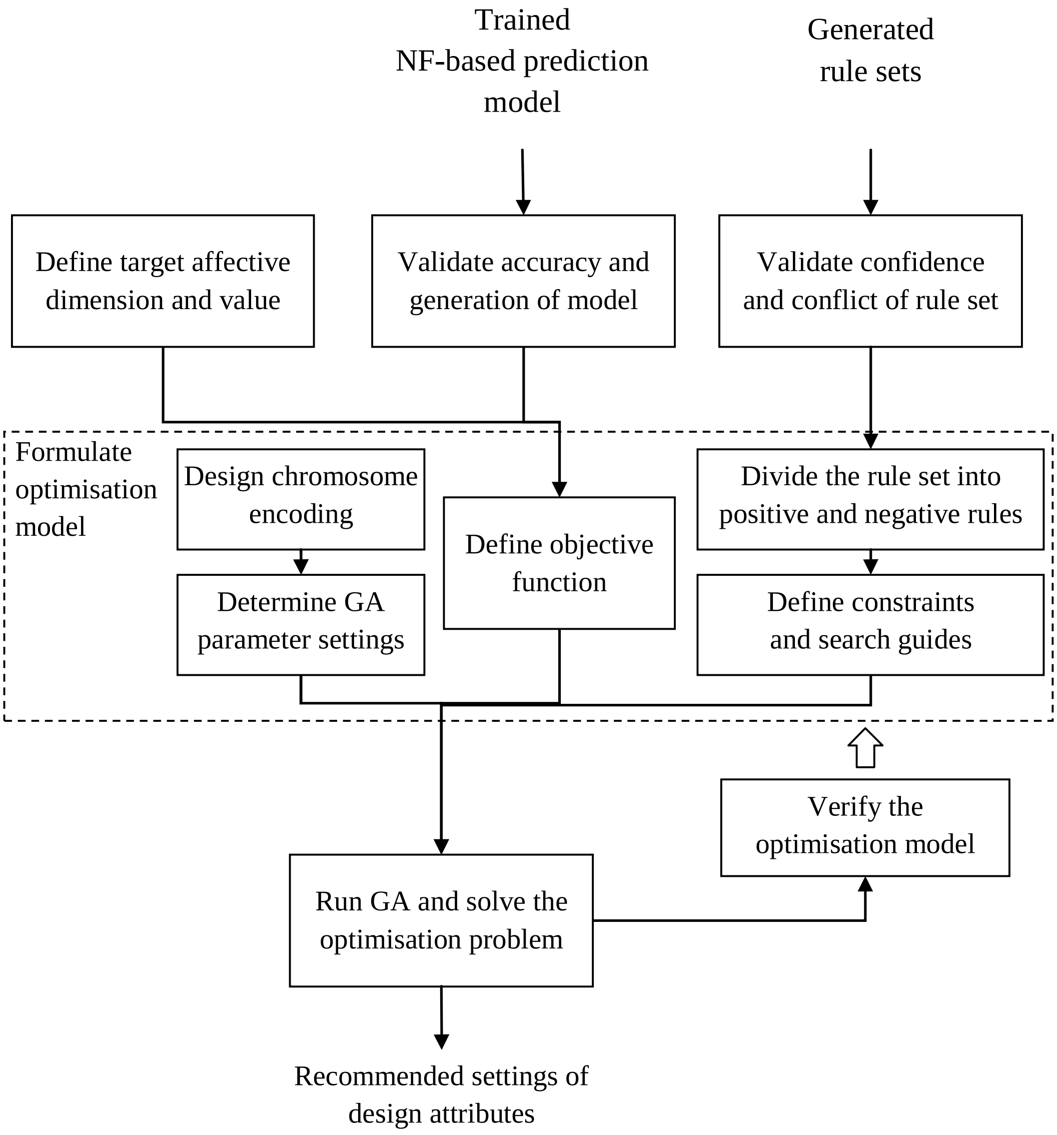

Trained NF-based prediction model
Generated rule sets
Define target affective dimension and value
Validate accuracy and generation of model
Validate confidence and conflict of rule set
Formulate optimisation model
Design chromosome encoding
Determine GA parameter settings
Define objective function
Divide the rule set into positive and negative rules
Define constraints and search guides
Verify the optimisation model
Run GA and solve the optimisation problem
Recommended settings of design attributes

Figure 3.3 Formulation of design optimisation model

Chapter 4 Design and Development of an Intelligent System for Supporting Affective Design

This chapter describes the design and development of the architecture of the proposed intelligent system for supporting affective design. The architecture includes three models, namely, a MOGA-based rule-mining model, a dynamic NF model, and a design optimisation model.

4.1 Architecture of the intelligent system

Figure 4.1 shows the architecture of the proposed intelligent system for supporting knowledge discovery and optimisation in the affective design of products. The proposed system mainly contains three models: a MOGA-based rule-mining model, a dynamic NF model, and a design optimisation model. The rule-mining model aims to search for the preferred design patterns globally using a MOGA approach. The preferred design patterns can be used as inference rules for classifying the levels of customer affection approximately using a rule-based system. The dynamic NF model aims to develop prediction models for relating design attributes and customer affection using a Dynamic Evolving Neuro-Fuzzy System (DENFIS) approach. The design optimisation model is used to search for the optimal design attribute settings using the generated rules and models. The mined rules are used to guide the search, and the developed NF model is used to predict the customer affections of candidate solutions. The next sections describe the details of individual models.

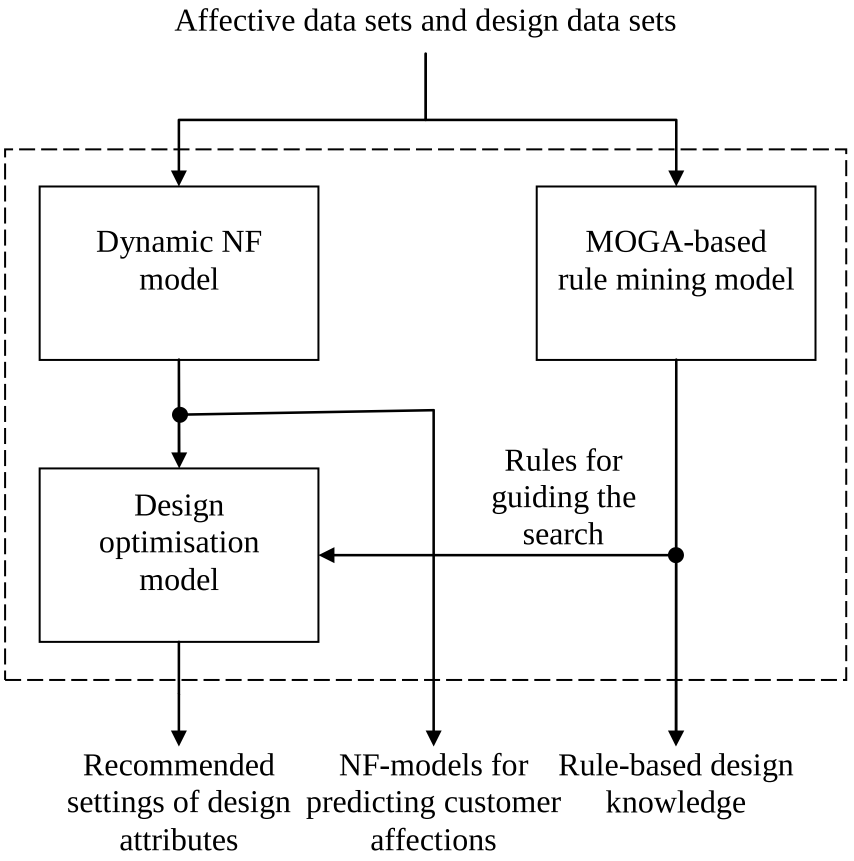

Affective data sets and design data sets
Dynamic NF model
MOGA-based rule mining model
Design optimisation model
Rules for guiding the search
Recommended settings of design attributes
NF-models for predicting customer affections
Rule-based design knowledge

Figure 4.1 Architecture of the proposed intelligent system

4.2 Multi-objective genetic algorithm based rule-mining model

A novel two-stage rule-mining approach to affective design based on MOGA is proposed. The concepts of preference order and approximate rule are adopted to deal with the ordinal nature and ambiguous relations within affective data, respectively. The approach is designed to generate rules that can determine the lower and upper approximations of customer affections induced by design patterns. The detailed design of the MOGA and the process of rule generation are described as follows.

4.2.1 Rule mining for affective design

Rule mining for affective design of products involves the extraction of informative patterns, which describe the relationships between design attributes and customer affection from raw data sets of market surveys and the translation of the patterns into decision rules. Similar to the association rule-based Kansei mining system proposed by Jiao *et al*. (2006), the proposed approach takes advantage of the use of raw data sets of market surveys in the rule-mining process. By treating raw data, it avoids information loss caused by the use of average values in conventional Kansei statistical analyses (Aktar Demirtas *et al*., 2009).

As customer affections towards affective design are always ambiguous, a rule-mining method was developed in this research to generate approximate rules. Different from crisp rules, design patterns induce approximate rules to admit the estimation of lower and upper limits of ambiguous customer affection. The proposed rule-mining approach is more appropriate in dealing with ambiguous data sets. The difference between the lower and upper limits reflects the discrepancy or inconsistency of customer feelings.

As customer evaluation surveys typically use the SD scale, the collected rating scores of customer affections are ordinal. The concept preference order adopted in the current research represents the outranking relation for the ordinal ratings of customer affections (Zhai *et al.*, 2009b). As an example, consider an SD scale containing three rating levels, namely, ‘simple’, ‘normal’, and ‘complex’ for evaluating a product design. ‘Simple’ outranks ‘normal’, and ‘normal’ outranks ‘complex’ if a respondent prefers a simpler design and vice versa. Conventional multi-class mining techniques are not suitable because the ratings are assumed discrete and independent values. To represent the outranking relation, the design of the proposed rule-mining method enables the computation of the ratings based on union sets instead of discrete levels. Aside from rule accuracy and comprehensibility, an additional criterion was introduced to rationalise the outranking relation that exists in customer evaluation data.

In the present study, the structure of an approximate rule is based on the 'IF-THEN' rule. The rule antecedent (IF-part) describes the settings of the design attributes. Every design attribute is defined as a rule condition. Rule consequence refers to a decision attribute, in which it is particularly defined for approximating the customer affection, ψ. Given that a design profile frequently combines categorical attributes with quantitative attributes, the developed method should be able to deal with the two kinds of design attributes simultaneously. A chromosome-encoding scheme was proposed to deal with the two kinds of attributes, determine the approximations, and represent an approximate rule. The details of the scheme are described in Section 4.2.4. An approximate rule can be expressed as follows:

$$\text{Rule } R\text{: IF } A_p \in x_{p,l} \wedge \cdots \wedge A_P \in x_{P,l} \wedge A_q \in \left[v_q^{lower}, v_q^{upper}\right] \wedge \cdots \wedge A_Q \in \left[v_Q^{lower}, v_Q^{upper}\right], \text{THEN } \psi \, \boldsymbol{Op} \, \psi_L \text{ with } w_{(R)} \text{ and } CF_{(R)}$$

where A_p and A_q denote the pth categorical attribute and qth quantitative attribute, respectively, for $p = \{1, 2, \cdots, P\}$ and $q = \{1, 2, \cdots, Q\}$, P and Q are the number of categorical and quantitative attributes, respectively, $x_{i,l}$ represents lth item of the pth categorical attribute, for $l = \{1, 2, \cdots, L_p\}$, v_q^{lower} and v_q^{upper} are the lower and upper values of qth quantitative attribute, $\boldsymbol{Op}$ is a relational operator (either ≤ or ≥), ψ is the approximation of customer affection, ψ_L is the level of customer affection in an SD or

Likert scale, $w_{(R)}$ is the weight of the single rule, and $CF_{(R)}$ is the confidence factor of the single rule.

4.2.2 MOGA for rule mining

The process of rule mining involves two procedures: rule evaluation and rule selection. The process can be considered as an optimisation problem that aims to find the best rules according to the criteria of rule mining. GA-based data mining has been attempted in the area of knowledge discovery (de la Iglesia *et al*., 2003) because it has the advantages of the population-based search to enumerate rule candidates as well as optimises the rule set. The fittest rules are reversed in the final population, whereas trivial rules are discarded in the evolution by applying an elitist GA. Applying GA to rule mining is deemed valuable for its robustness in performing a global search in rule space compared with traditional optimisation techniques that perform local search (Freitas, 2002). Moreover, GAs can integrate with other rule-mining techniques, such as association rules (Yan *et al*., 2009). However, various criteria of rule mining are common in rule evaluation. For example, accuracy, confidence and support are typical criteria used in rule mining. However, a rule-mining problem frequently encounters a trade-off among the multiple criteria of rule mining, such as the trade-off between rule accuracy and comprehensibility (Ghosh and Nath, 2004). To deal with such multiple criteria trade-off problems, MOGAs are considered (Konak *et al*., 2006). Most MOGAs apply Pareto-ranking techniques and obtain a non-dominated solution set of a multi-objective optimisation problem. Therefore, in the present research, the proposed MOGA-based rule-mining method can find a set of optimal trade-offs (a non-dominated solution set) based on several criteria of rule mining. MOGAs have been adopted in mining association rules (Ghosh and Nath, 2004) and classification rules (Dehuri *et al*., 2008; Kaya, 2010). Ghosh *et al.* (2004) employ a MOGA for association rule mining based on the three criteria of rule quality, namely, predictive accuracy, comprehensibility, and interestingness. Kaya (2010) developed an autonomous classifier using MOGA and applied the criteria of classification accuracy, average support, and understandability for classification rule mining. The use of MOGAs in rule mining can overcome the difficulty of specifying user-defined support and confidence thresholds. In traditional association rule mining, MOGAs can determine the fittest rules with yielding maximum rule accuracy (Yan *et al*., 2009).

To obtain knowledge about the affective design of products, the proposed MOGA-based rule-mining model was developed with particular attention to the relationships between design attributes and customer affections. Fast non-dominated sorting GA (NSGA-II), one type of MOGAs, is used in this research (Deb *et al*., 2002). NSGA-II is an effective algorithm that performs an elitist approach and a fast-sorting algorithm to rank individuals into the Pareto fronts. This well-known MOGA is used as a benchmark of MOGAs (Dehuri *et al*., 2008). According to Coello (2006), NSGA-II has higher computational efficiency than other MOGAs, such as strength Pareto evolutionary algorithm and Pareto Archive Evolution Strategy. NSGA-II can maintain good diversity along the Pareto optimal front using distance tournament selection and by measuring the crowding distance between each individual and its neighbours. This capability enables higher priority in selecting less crowded non-dominated solutions to the non-dominated set of the next generation, thus maintaining an even distribution of solutions along the Pareto optimal front. NSGA-II has been applied in association rule mining (de la Iglesia *et al*., 2003). For approximate rule mining, the NSGA-II can be employed to simultaneously consider the accuracy, comprehensibility, and definability of approximate rules. Generally, MOGAs require higher computational time compared with traditional single-objective GA. To improve the performance of MOGAs, a two-stage MOGA-based rule-mining approach is proposed in this study. Individual rules can be generated expeditiously using a simple chromosome design at the first stage of rule mining, and entire rule sets are refined at the second stage of rule mining.

4.2.3 Encoding of attributes

A chromosome-encoding scheme was proposed to represent a solution of an approximate rule for affective design. The proposed scheme can represent a solution that involves both categorical and quantitative attributes, as affective design commonly involves the two kinds of design attributes. The scheme enables the determination of lower and upper approximations of customer affections induced by the design attributes to form approximate rules.

(a) Categorical and quantitative attributes

GA can deal with problems that involve both categorical and quantitative attributes. In this study, a category attribute is encoded using a bit vector, as shown in Figure 4.2. Each bit of the bit vector represents an option of the categorical attribute. When categorical attribute, A_p, contains L_p items, it can be translated to a vector with L_p bits. The *l*th item is the setting of the attribute if the *l*th bit is 1.

$x_{p,1}$	$x_{p,2}$	…	$x_{p,l}$	…	x_{p,L_p}
0	0	…	1	…	0

Figure 4.2 Encoding scheme for the categorical attribute (Gene X_p)

A quantitative attribute can be represented by the lower and upper limits of its domain interval, $[v_q^{lower}, v_q^{upper}]$. For each quantitative attribute, two real numbers store the interval limits in a chromosome, as shown in Figure 4.3.

v_q^{lower}	v_q^{upper}
Real number 1	Real number 2

Figure 4.3 Encoding scheme for the quantitative attribute (Gene X_q)

(b) Decision attributes

According to previous works, a decision attribute can be either included or excluded in the chromosome design. Dehuri *et al.* (2008) employed an elitist multi-objective genetic algorithm in classification rule mining. In their work, a chromosome structure without a genome representing rule decision was used, such that the mining process was repeated in each decision class to obtain individual solutions. The solutions of all decision classes were then gathered to become a solution set of the multi-class problem. Although this method ensures that a global solution can be found, it requires large computational cost and time. An alternative method is to include a genome for representing the rule decision in the chromosome (Kaya, 2010). The main advantage of the alternative method is that the decision class of the rules can be determined using MOGA in a single run.

In the current research, two values of decision attributes are required to be determined. A genome is applied to represent a decision attribute in the chromosome, such that the values of the decision attribute can be found automatically in the rule-mining process. The genome, representing the rule decision, consists of a binary bit and a real number that denote the relational operator, ***Op***, and the approximate value, ψ_L, respectively, as shown in Figure 4.4. The approximation of customer affection, ψ, is determined by comparing it with customer affection, y_l, of raw data instance l during the rule-mining process. The relational operator ***Op*** is used to classify a rule to express either the lower or the upper union of the outranking relationships. If the bit of ***Op*** is encoded to 1, the relationship is defined as $y \leq \psi$, i.e., $\psi = \psi_{min}, \dots, \psi_{L-1}, \psi_L$, and the upper limit, ψ^{upper}, will be found. The bit of *Op* is 0 to find the lower limit, ψ^{lower}, and it represents the relationship of $\psi \geq \psi_L$, i.e., $\psi = \ \psi_L + \psi_{L+1}, \dots, \psi_{max}$. ψ_{min}, and ψ_{max} are the minimum and maximum levels in response to the SD scale for collecting customer affection, respectively.

Op	ψ_L
≤ or ≥	Real number

Figure 4.4 Encoding scheme for the quantitative attribute (Gene *Y*)

4.2.4 Two-stage rule mining

Based on the encoding scheme of a GA population, GA-based rule mining can be categorised into two groups: the Michigan and Pittsburgh approaches (Freitas, 2003). In the Michigan approach, each chromosome of the population represents a single rule as part of a candidate solution (Dehuri *et al.*, 2008). In the Pittsburgh approach, each chromosome represents a set of rules as an entire candidate solution. The former approach is effective in implementing GA rule mining. The latter approach is more complicated and takes longer computational time, but it is better than the former in finding solutions when considering rule interaction .

In this research, the proposed two-stage rule-mining approach captures the advantages of both the Michigan and the Pittsburgh approaches. Figure 4.5 shows the two-stage rule mining using MOGA for affective design. The first stage of rule mining aims at promptly generating a set of individual rules using the Michigan approach, and the second stage refines the entire rule set based on the Pittsburgh approach. The rules obtained from the first stage are used to initiate the rule sets at the second stage of rule mining. At the second stage, an initial population can be generated, which is close to the optimal solution of the rule set. First, the weights of the rules are set randomly to maintain the diversity of the initial population. Then, the genes representing rule attributes are further varied by mutations, such that the global search can persist. The method can help reduce the computational time of rule mining based on the Pittsburgh approach and maintain a global search for an optimal solution. The two-stage approach is more effective in generating rule sets considering the rule interaction compared with the Pittsburgh approach with random initialisation.

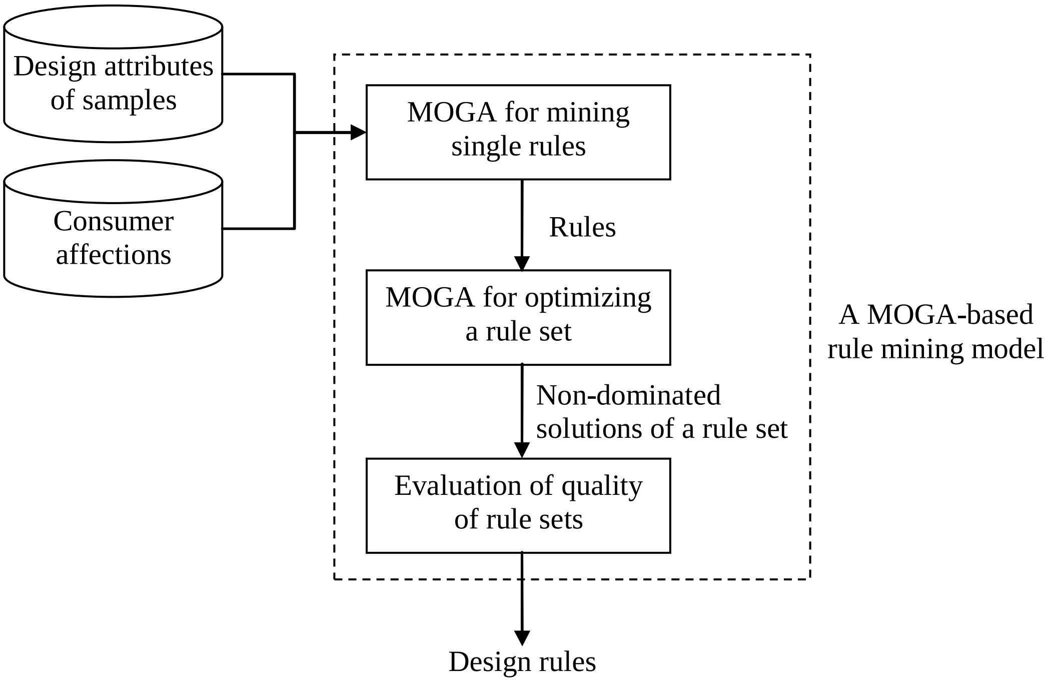

Design attributes of samples
Consumer affections
MOGA for mining single rules
Rules
MOGA for optimizing a rule set
Non-dominated solutions of a rule set
Evaluation of quality of rule sets
A MOGA-based rule mining model
Design rules

Figure 4.5 Two-stage MOGA-based rule mining for affective design

Regarding the chromosome design of the two-stage MOGA-based rule mining at the first stage, a chromosome consists of genomes for categorical, quantitative, and decision attributes, and an additional genome for a set of activation flags, as shown in Figure 4.6. As the number of design attributes is usually predefined in an affective design study, a fixed-length chromosome is selected to encode a rule in the proposed rule-mining approach. The binary activation flags, a_p and a_q, are used to achieve the variable-length rule mining with the fixed-length chromosome, such that the involvement of rule conditions and the length of rule can be controlled. In other words, the number of activation flags is set as the number of design attributes.

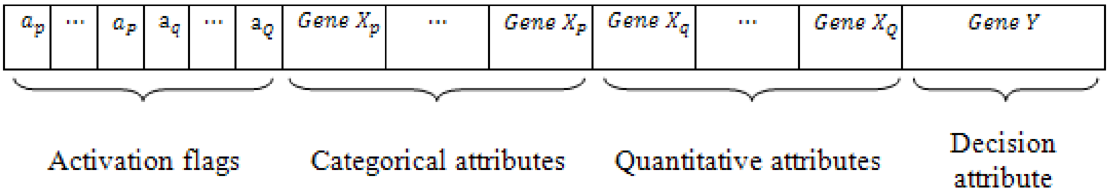


Figure 4.6 Chromosome structure at the first stage of rule mining

At the second stage of rule mining, MOGA is also applied, but it aims to optimise a rule set instead of mining individual rules. The chromosome structure divides into two parts to represent a set of weights and a set of individual rules. Each rule, R_m, is associated with a weight, w_m, where $m = \{1, 2, \cdots, M\}$, and M is the total number of rules. The range of w_m is between 0 and 1. In this research, the weights and the set of rules are encoded in a fixed-length chromosome. The function of a weight is to determine the activation and the significance of the corresponding rule. A rule, R_m, is selected as an activated rule, R_α, if its weight, w_m, is greater than the user-defined threshold, τ. Otherwise, the rule is excluded from the rule set. The value of τ can be defined between 0 and 1.

A chain of the chromosomes of individual rules represents the rule set. This chain has the same encoding scheme of chromosomes as those at the first stage of rule mining. The chromosome design enables the further refinement of the internal values of the rules. The size of the rule set, *M*, is determined by the number of single rules generated at the first stage of rule mining. Figure 4.7 shows the chromosome structure at the second stage of rule mining.

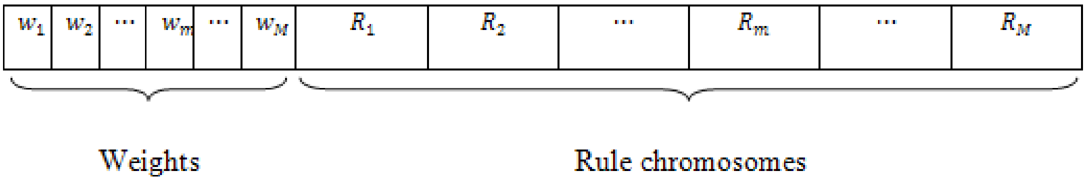


Figure 4.7 Chromosome structure at the second stage of rule mining

4.2.5 Crossover and mutation operations for categorical and quantitative attributes

The chromosome design of the proposed rule-mining approach combines binary with real-coded genes. Binary bits represent the activation flags and categorical attributes, whereas the weights and quantitative attributes are encoded using real numbers in a chromosome. Thus, two different genetic operators are required for crossover and mutation of the two types of data. A two-point crossover operator and a bitwise mutation operator, as shown in Figures 4.8 and 4.9, respectively, are used to deal with the binary-coded parts, a_p, a_q , and $Gene\ X_p$. Simulated binary crossover and polynomial mutation (Agrawal *et al.*, 1995; Deb *et al.*, 2002) are adopted for the genetic operation of the real-coded parts, $Gene\ X_q$, $Gene\ Y$, and w_m. The simulated binary crossover performs an arithmetic crossover with a random distribution for *d*th real number. It is given as follows:

$$\boldsymbol{c}_{\boldsymbol{1},\boldsymbol{d}} = \frac{1}{2}\left[(1-\zeta_d)\boldsymbol{p}_{1,d} + (1+\zeta_d)\boldsymbol{p}_{2,d}\right] \qquad (1)$$

$$\boldsymbol{c}_{\boldsymbol{2},\boldsymbol{d}} = \frac{1}{2}\left[(1+\zeta_d)\boldsymbol{p}_{1,d} + (1-\zeta_d)\boldsymbol{p}_{2,d}\right] \qquad (2)$$

where $\boldsymbol{c}_{1,d}$ and $\boldsymbol{c}_{2,d}$ are the values of the new children for dth real number, $\boldsymbol{p}_{1,d}$ and $\boldsymbol{p}_{2,d}$ are the values of the selected parents, and ζ_d is generated with a random number ξ_d between [0, 1] and is given as follows:

$$\zeta_d = (2\xi_d)^{\frac{1}{\eta_c+1}},\ if 0 \leq \xi_d \leq 0.5 \tag{3}$$

$$\zeta_d = \frac{1}{[2(1-\xi_d)]^{\frac{1}{\eta_c+1}}},\ if\ \xi_d > 0.5 \tag{4}$$

where η_c is a distribution index that determines the deviation of the children from their parents.

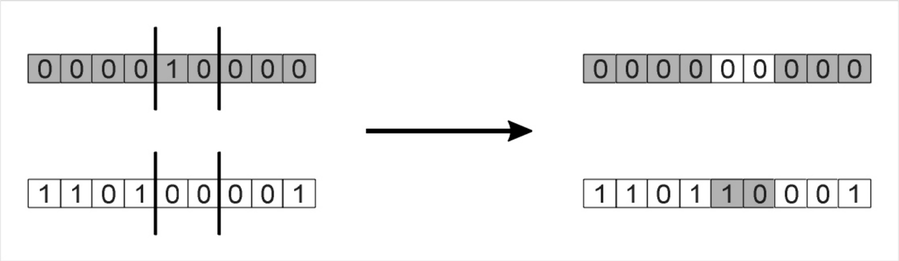


Figure 4.8 Two-point crossover operator for the binary-coded part

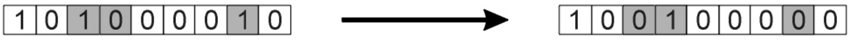


Figure 4.9 Bitwise mutation operator for the binary-coded part

The polynomial mutation enables a global search for the quantitative attributes using GA. It is given as follows:

$$\boldsymbol{c}_d = \boldsymbol{p}_d + (\lambda_d^{upper} - \lambda_d^{lower})\delta_d \tag{5}$$

where c_d and p_d are the child and parent of the dth real number, respectively, λ_d^{upper} and λ_d^{lower} are the upper and lower bounds, respectively, and δ_d is the changing rate derived from a polynomial distribution and is defined as follows:

$$\delta_d = (2\xi_d)^{\frac{1}{\eta_m+1}} - 1, \qquad if\ \xi_d < 0.5 \tag{6}$$

$$\delta_d = 1 - [2(1-\mu_d)]^{\frac{1}{\eta_m+1}},\ \ if\ \mu_d \geq 0.5 \tag{7}$$

where η_m is a mutation distribution index.

4.2.6 Objective functions

The formulation of objective functions, also called fitness functions, is an important process in applying MOGA. Rule-mining problems frequently involve multi-objectives while considering various criteria of rule mining. Accuracy is a fundamental criterion for measuring rule quality in rule mining. A generated rule is also required to make it understandable and interesting to the user (Ghosh and Nath, 2004). As a complex rule is difficult to understand, the ideal length of a rule is about two or three conditions in the rule antecedent (Freitas, 2002). A good rule should consider user interest. Users usually hope to discover unexpected knowledge from the rules. As a result, a rule-mining problem can be considered a multi-objective optimisation problem in which the accuracy, comprehensibility, and interestingness of rules are investigated.

Rule mining is typically searches frequent examples from the data. Confidence is used to measure the rule accuracy by estimating the percentage of the number of examples in data sets that fulfil the rule conditions or statements. The confidence of a single rule is defined as follows:

$$Conf(R) = \frac{|X \cup Y|}{|X|} \tag{8}$$

where $|X \cup Y|$ is the number of examples satisfying the statement of both rule antecedent, X, and rule consequence, Y, and $|X|$ is the number of examples satisfying the rule antecedent only.

The accuracy of a rule set can be estimated by the overall accuracy of the rule interaction. A rule set, S, is used to classify an example z, and it yields an aggregate decision, ψ_{A} , which is defined by its lower approximation, ψ_A^{lower} and upper approximation, ψ_A^{upper}. Figure 4.10 shows an example of the formation of an aggregate decision. The values of $\psi_A^{lower}$and $\psi_A^{upper}$are determined using a weighted voting based on the weighted confidence of all activated rules in the rule set S. For rules having the same ψ_L for ψ^{lower}, the sum of the weighted confidence of those rules is computed as

$$\text{For } \forall R_{\alpha,L} \in R_{\alpha}: \psi^{lower} = \psi_L, \qquad Vote(\psi_A^{lower} = \psi_L) = \sum^{|R_{\alpha,L}|} w_{(R_{\alpha,L})} \times CF_{(R_{\alpha,L})} \tag{9}$$

where $Vote(\psi_A^{lower} = \psi_L)$ donates the magnitude of choosing the level ψ_L as the aggregate decision ψ_A^{lower}, $\left|R_{\alpha,L}\right|$ refers to the number of rules that are activated and contains the decision of $\psi^{lower} = \psi_L$, and $CF_{(R_{\alpha,L})}$ is the confidence factor of the rule.

The winner class of ψ_A^{lower} is then determined by finding the level ψ_L, which has the maximum$\left[Vote\left(\psi_A^{lower} = \psi_L\right)\right]$. The overall decision of ψ_A^{upper} is determined by the same voting method.

The weighted confidence is introduced at the second stage of rule mining for better consideration of the rule interactions. The weights of rules are the parameters encoded in the chromosome. They are randomly initialised and then optimised by the MOGA. The results reflect the importance of a single rule and control the interactions of the rules within a rule set. The confidence factors indicate the accuracy of the single rules. The confidence factor of each rule is computed during the evaluation of the objective functions of the children solutions. A rule with high confidence is sometimes specified for particular cases, but it lacks generalisation. A generalised rule often covers more cases and has a higher support rate but less confidence. The weighted confidence can balance the specificity and the generalisation of the rules in the rule set.

The rule set S is tested by comparing the resulting approximation with the actual affective rating, y_l, of data instance l; i.e., S is true for the data instance l, if $\psi_A^{lower} \leq y_l \leq \psi_A^{upper}$. The accuracy of a rule set is defined as follows:

$$Acc(S) = \frac{Number\ of\ truly\ classified\ data\ instances}{Number\ of\ data\ instances} \qquad (10)$$

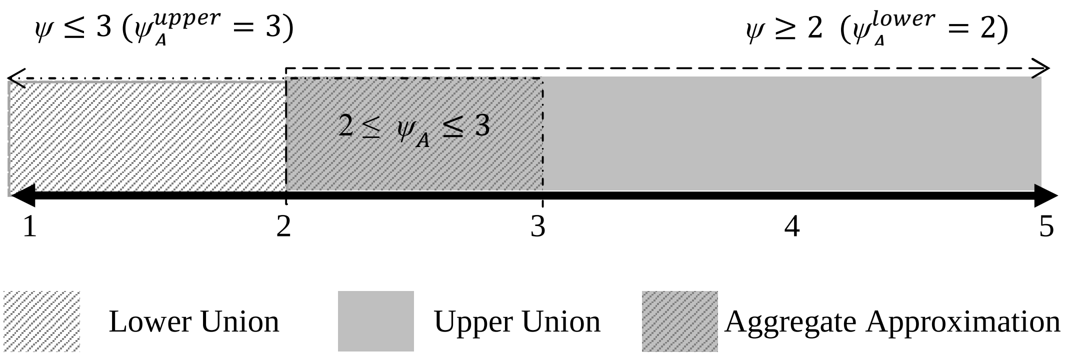

$\psi \leq 3$ ($\psi_A^{upper} = 3$)
$\psi \geq 2$ ($\psi_A^{lower} = 2$)
$2 \leq \psi_A \leq 3$
1
2
3
4
5
Lower Union
Upper Union
Aggregate Approximation

Figure 4.10 Example of the formation of an aggregate decision from approximate rules

Comprehensibility indicates the simplicity of the rule structure. The complexity of a rule increases when the number of attributes of the rule increases. The complexity of a rule is defined as follows:

$$Cmplx(R) = \ Number\ of attributes\ included\ in\ rule\ R \qquad (11)$$

where $Cmplx(R) \ \geq 1$.

As aforementioned, a set of activation flags controls the length of a rule in the chromosome-encoding scheme. The complexity of a rule is measured by counting the number of positive flags at the first stage of mining. At the second stage, only activated rules R_α are included in a rule set if their weights are greater than their threshold, τ. The complexity of a rule set can then be defined as

$$Cmplx(S) = \ |R_\alpha| \ + \sum^{|R_\alpha|} Cmplx(R_\alpha) \qquad (12)$$

where $Cmplx(S) \ \geq 1$.

The comprehensibility of the rule set S can be defined as follows:

$$Comp(S) = \frac{1}{Cmplx(S)} \tag{13}$$

Users are interested in a rule if it can indicate important information and if it has high confidence (Ghosh and Nath, 2004). The interestingness of a rule, $Int(R)$, can be defined as follows:

$$Int(R) = \frac{|X \cup Y|}{|X|} \times \frac{|X \cup Y|}{|Y|} \times \left(1 - \frac{|X \cup Y|}{Number\ of\ examples}\right) \tag{14}$$

In addition, interestingness indicates the definability of approximate rules. As the decision of approximate rules is defined in terms of lower and upper approximations, the decision value is indefinite or roughly definable if the lower and upper approximations are not equal. A decision with a huge difference between the lower and upper approximations may be indefinite, and the rule may be too rough and trivial for further use. The definability of a rule is measured by the extent of the approximation, which can be defined as

$$\mathit{\Delta}\psi = \psi^{upper} - \psi_{min} + 1, \text{for a rule determining } \psi^{upper} \tag{15}$$

$$\mathit{\Delta}\psi = \psi_{max} - \psi^{lower} + 1, \text{for a rule determining } \psi^{lower} \tag{16}$$

$$Def(R) = 1 - \frac{\mathit{\Delta}\psi - \psi_{min}}{\psi_{max} - \psi_{min}} \tag{17}$$

Definability can be measured with the extent of aggregate approximation, $\mathit{\Delta}\psi_A$, which is given by

$$\mathit{\Delta}\psi_A = \psi_A^{upper} - \psi_A^{lower} + 1 \tag{18}$$

The definability of the approximation can be defined as

$$Def(\psi_A) = 1 - \frac{\Delta\psi_A - \psi_{min}}{\psi_{max} - \psi_{min}} \tag{19}$$

The definability of a rule set S can be measured using the average $Def(\psi_A)$ for all examples within the data set. It is defined as follows:

$$Def(S) = \frac{1}{n} \times \sum_{l=1}^{n} Def(\ \psi_A)_l \tag{20}$$

where n represents the number of data within the data set, and $Def(\ \psi_A)_l$ is the $Def(\psi_A)$, which is obtained when data instance *l* is classified by the rule set S.

To summarise, the objective function of extracting individual rules at the first stage of rule mining is to *maximise*$\{Conf(R);\ Int(R);\ Def(R)\}$, and the objective function of refining the rule set at the second stage is to *maximise*$\{\ Acc(S);\ Comp(S);\ Def(S)\}$.

The basic goal is to provide reliable and valuable decision support information for affective design. The accuracy and definability of rules have a higher priority than comprehensibility in this study. However, there is a trade-off between accuracy and definability of rules. Users are required to consider the balance between accuracy and definability when the optimal rules are selected from a Pareto optimal solution set.

4.3 Dynamic neuro-fuzzy model

In this research, a dynamic NF approach is proposed to model the relationships between design attributes and customer affections using a modified DENFIS. Figure

4.11 shows the architecture of the dynamic NF model for affective design. The DENFIS-based model enables fast incremental learning by applying evolving clustering method (ECM) and recursive least squares (RLS). For affective design, DENFIS is modified by applying RLS with the variable forgetting factor, such that the modified DENFIS can effectively generate new prediction models by updating data sets.

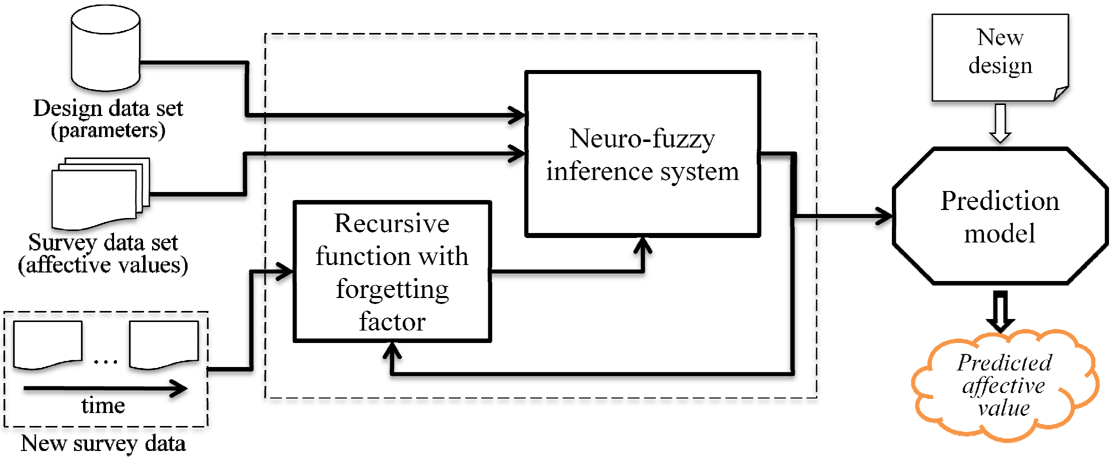


Figure 4.11 A dynamic NF model for affective design

4.3.1 Dynamic evolving neuro-fuzzy inference system

DENFIS is a TSK NF model with local generalisation for modelling dynamic effects and predicting time-series problems (Kasabov and Qun Song, 2002; Kasabov *et al.*, 2008). DENFIS is a fast and accurate algorithm for both online and offline learning compared with other popular NF models, such as ANFIS. ANFIS is also a TSK NF model, but its fixed structure hinders it from adapting to new data sets. In addition, ANFIS cannot be used for high dimensional problems (Kasabov, 2007a), as the complexity of ANFIS models typically grows exponentially with the number of input attributes. The number of rule nodes generated in an ANFIS structure is equal to

$\prod_{j=1}^{J} N_{MF,j}$, where $N_{MF,j}$ donates the number of MF for jth attribute, and J is the number of input attributes of the NF model. For instance, the ANFIS structure contains 6,561 (=3^8) rule nodes if there are eight attributes, and each attribute contains three MFs. Too many attributes and MFs cause difficulty in computation because of insufficient machine memory (Zadeh and Berkeley, 2001). In contrast, DENFIS can generate a streamlined model. A reasonable number of fuzzy rule-based models can be created according to the dynamic clustering of input spaces using ECM. Thus, several local models can address the problem domain

The ECM is a fast and one-pass online incremental clustering algorithm used in DENFIS (Kasabov and Qun Song, 2002; Kasabov, 2007b). The method partitions the data points into clusters, which are specified by the centres and the radii. The number of clusters created by ECM is self-determined according to a threshold value, D_{thr}. The parameter controls the maximum distance between a data point of a cluster and the cluster centre, and acts as a constraint for updating the radii of the clusters. In the clustering process, the ECM starts with initialising the first cluster, C_1, with the first data point, Z_1; i.e., K = 1, where K is the number of clusters created by ECM. When a new data instance, Z_n, is presented, its distance to the cluster centre, c_k, of each existing cluster, C_k, is computed, where $k = 1,2, \dots, K$. Hence, the distance D' between data Z_n and its closest cluster C' is found. The new point belongs to the cluster C', and no update occurs for $D' < r'$, where r' denotes the current radius of the cluster C'. Otherwise, if $D' < D_{thr}$, the centre, c', and radius, r', of the closest cluster C' are updated (Kasabov and Qun Song, 2002). If not, a new cluster, C_{K+1}, is created at the data point Z_n, such that $K = K + 1$. Thus, online data can be dynamically grouped by applying the ECM. This step facilitates the formulation of the optimal number of local models for modelling substantial data effectively.

A fuzzy rule-based model is created for each cluster after determining the partitions of the input space by the clustering process. A fuzzy rule-based model consists of fuzzy numbers of input attributes in the rule antecedent and a TSK first-order model in the rule consequent. The form of fuzzy rule-based models can be expressed as follows:

$$\begin{cases} \text{IF } x_1 \text{ is } MF_{11} \text{ and } x_2 \text{ is } MF_{21} \text{ and} \ldots \text{and } x_J \text{ is } MF_{J1,} \text{ THEN } y \text{ is } f_1(x_1, x_2, \ldots, x_J) \\ \text{IF } x_1 \text{ is } MF_{12} \text{ and } x_2 \text{ is } MF_{22} \text{ and} \ldots \text{and } x_J \text{ is } MF_{J2,} \text{ THEN } y \text{ is } f_2(x_1, x_2, \ldots, x_J) \\ \vdots \\ \text{IF } x_1 \text{ is } MF_{1K} \text{ and } x_2 \text{ is } MF_{2K} \text{ and} \ldots \text{and } x_J \text{ is } MF_{JK,} \text{ THEN } y \text{ is } f_K(x_1, x_2, \ldots, x_J) \end{cases}$$

where x_j is $MF_{jk}, j = 1,2, \ldots, J;\ k = 1,2, \ldots, K$. MF_{jk} denotes a Gaussian MF used for fuzzification of input conditions, J is the number of input attributes, K is the number of clusters results by ECM, and $f_k(x_1, x_2, \ldots, x_J)$ denotes the function of a first-order linear model.

In DENFIS, input space is fuzzified according to the clustering results of ECM. For each cluster, the cluster centre c_k and radius r_k are assigned as parameters μ and σ of the Gaussian function, respectively. Gaussian MF is defined as follows:

$$Gaussian\ MF = \alpha\, exp\left[-\frac{(x-\mu)^2}{2\sigma}\right] \tag{21}$$

For the rule consequent of each fuzzy rule, a first-order linear model is generated and updated using a weighted recursive least square (WRLS) with forgetting factor in the DENFIS (Kasabov, 2002, 2007b). Each of the linear models can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_1 x_2 + \cdots + \beta_J x_J \tag{22}$$

For each rule, u data instances $\{[x_1^i, x_2^i, \ldots, x_j^i, \ldots, x_J^i], y_i\}$, where $i = 1,2, \ldots u$, belong to the same cluster. They are intended to be the initial training data for the RLS. For the initial linear model, regression coefficients of $\boldsymbol{\beta} = [\beta_0, \ \ \beta_1, \ \ \beta_2, \ \ \cdots, \ \ \beta_j \ \ \cdots, \ \ \beta_J]^T$ are calculated by applying the weighted least squares estimator using the following formulas:

$$\begin{cases} \boldsymbol{P} = (A^T W A)^{-1} \\ \boldsymbol{\beta} = \boldsymbol{P} A^T W y \end{cases} \tag{23}$$

where

$$A = \begin{pmatrix} 1 & x_1^1 & x_2^1 & \cdots & x_j^1 & \cdots & x_J^1 \\ 1 & x_1^2 & x_2^2 & \cdots & x_j^2 & \cdots & x_J^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & x_1^i & x_2^i & \cdots & x_j^i & \cdots & x_J^i \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & x_1^u & x_2^u & \cdots & x_j^u & \cdots & x_J^u \end{pmatrix} \tag{24}$$

$$y = [y_1 \quad y_2 \quad \cdots \quad y_i \quad \cdots \quad y_u]^T \tag{25}$$

and

$$W = \begin{pmatrix} \omega_1 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & \omega_2 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \omega_i & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & \omega_u \end{pmatrix} \tag{26}$$

where ω_i is $(1 - D_i)$, $i = 1, 2, \ldots, u$, and D_i is the distance between the ith data and the corresponding cluster centre.

The coefficient matrix $\boldsymbol{\beta}$ and inverse matrix $\boldsymbol{P}$ are used as initial values of future recursive calls. Let $\boldsymbol{\beta}_u$ and $\boldsymbol{P}_u$ be the last result obtained using least squares. When a new data pair is fed, the regression coefficient $\boldsymbol{\beta}_{u+1}$ is updated based on the following:

$$\begin{cases} \boldsymbol{\beta}_{u+1} = \boldsymbol{\beta}_u + \omega_{u+1}\boldsymbol{P}_{u+1}a_{u+1}(y_{u+1} - a_{u+1}^T\boldsymbol{\beta}_u) \\ \boldsymbol{P}_{u+1} = \dfrac{1}{\lambda}\left(\boldsymbol{P}_u - \dfrac{w_{u+1}\boldsymbol{P}_u a_{u+1} a_{u+1}^T \boldsymbol{P}_u}{\lambda + a_{u+1}^T \boldsymbol{P}_u a_{u+1}}\right) \end{cases} \tag{27}$$

where λ is a forgetting factor, $0 < \lambda \leq 1$, and

$$a_{u+1}^T = \begin{bmatrix} 1 & x_1^{u+1} & x_2^{u+1} & \cdots & x_j^{u+1} & \cdots & x_J^{u+1} \end{bmatrix} \tag{28}$$

Finally, an NF model can be created based on fuzzy rule-based models generated using ECM and WRLS. Figure 4.12 shows a typical structure of a five-layer NF model. BP algorithm can be used to further optimise the fuzzy MF of the NF model.

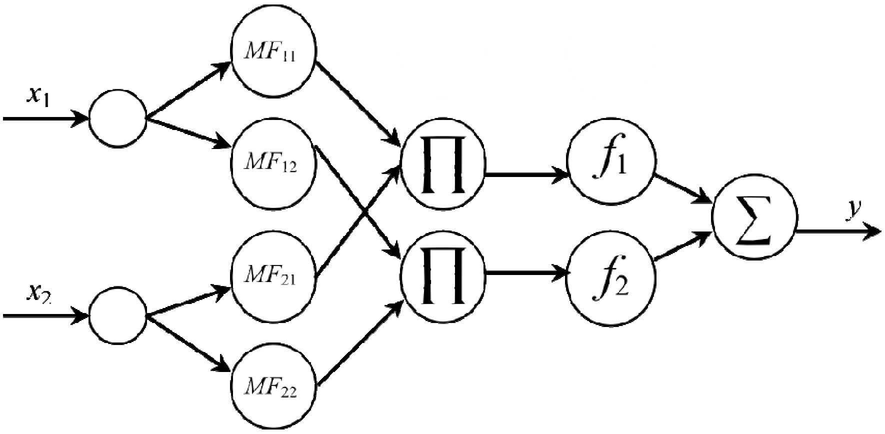


Figure 4.12 A five-layer structure of the dynamic NF model (*J*=2*, K=2*)

4.3.2 Modified DENFIS for affective design

The original DENFIS is a single-feed model. It can only be updated incrementally, and data pairs are inputted one by one. The influence of every data instance is typically decayed by applying RLS with a constant forgetting factor, λ, as shown in Figure 4.13. For affective design, some companies may conduct surveys several times over a period of time to obtain more accurate customer affection towards the designs of products. Let t be the period in which a respondent participates in a longitudinal survey. The respondent evaluates the design profiles of N product samples. The design profile of the nth product sample can be represented as $X(n) = \left[x_1^n, x_2^n, \dots, x_j^n, \dots, x_J^n\right]$, where $n = 1,2, \dots, N$. Subsequently, N customer affections are obtained from the survey. The affective data set collected at period t , $Y(t)$ contains $[y_1(t), y_2(t), \dots, y_N(t)]$, where $y_n(t)$ denotes affective rating acquired from the respondent towards N product samples. In other words, N data pairs are available for updating the DENFIS-based model after the $\imath$th survey.

A DENFIS model modification is proposed to process a batch of N data pairs for each update process. The modified DENFIS introduces the variable forgetting factor instead of the constant forgetting factor, such that the decay effect can be controlled by varying the forgetting factor λ. Typically, $\lambda < 1$ is used for RLS such that fresh data exert a greater influence than previous data during recursive calls, whereas previous and $X(n)$ current data are treated equally by RLS if $\lambda = 1$ (Zhuang, 1998). The forgetting factor value is switched during incremental learning of the modified DENFIS to update affective data sets from different periods of time.

The modified DENFIS was developed to decrease the influences of data sets by batch over time. When data set $Y(t)$ is available to the model, its influence is greater than that of the previous data set, $Y(t-1)$. However, the influence of data, $y_1(t), y_2(t), \dots, y_N(t)$, inside data set, $Y(t)$, should be equal because the data are in the same period. During the DENFIS training process, data $y_1(t), y_2(t), \dots, y_N(t)$ are partitioned into clusters based on ECM. For each cluster, the first-order model is updated with the data subset using RLS. When the first data of the subset, such as

$y_1(t)$, is proceeded, $\lambda < 1$ is set to exert the decay effect on previous data batches compiled as matrices β_{t-1} and P_{t-1}, where β_{t-1} and P_{t-1} have been obtained from previous RLS in the data batch $Y(t-1)$. For the remaining data of the data subset, $\lambda = 1$ is set to suspend the decay during the training sequence from $y_1(t)$ to $y_N(t)$. As a result, the previous data batch fades out while the current data batch is learned with the same influence. Staircase decay, as shown in Figure 4.14, can be obtained by the proposed batch incremental training process.

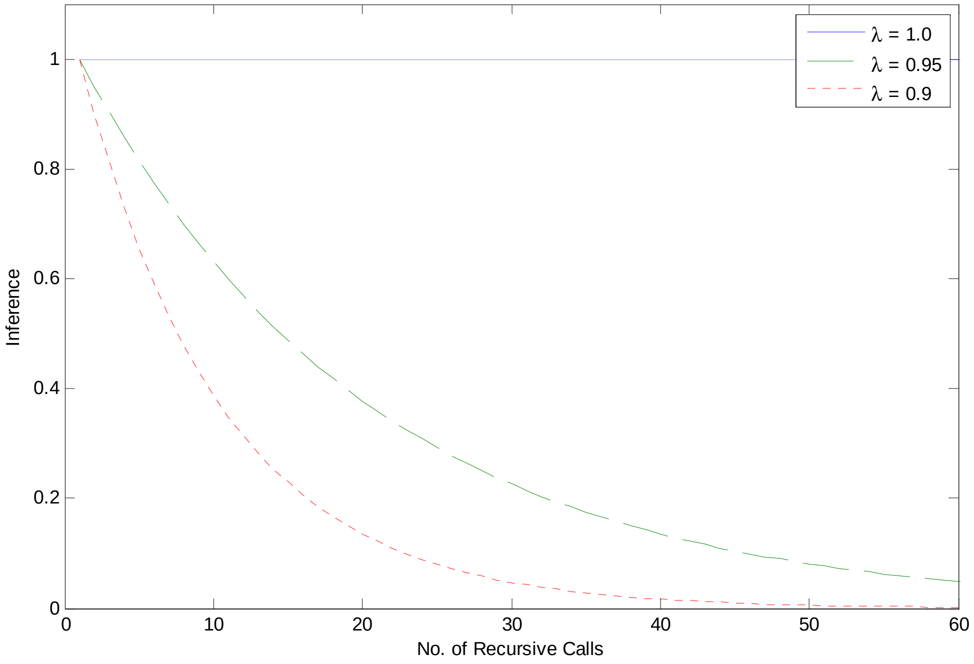


Figure 4.13 Decay of inference with a constant forgetting factor

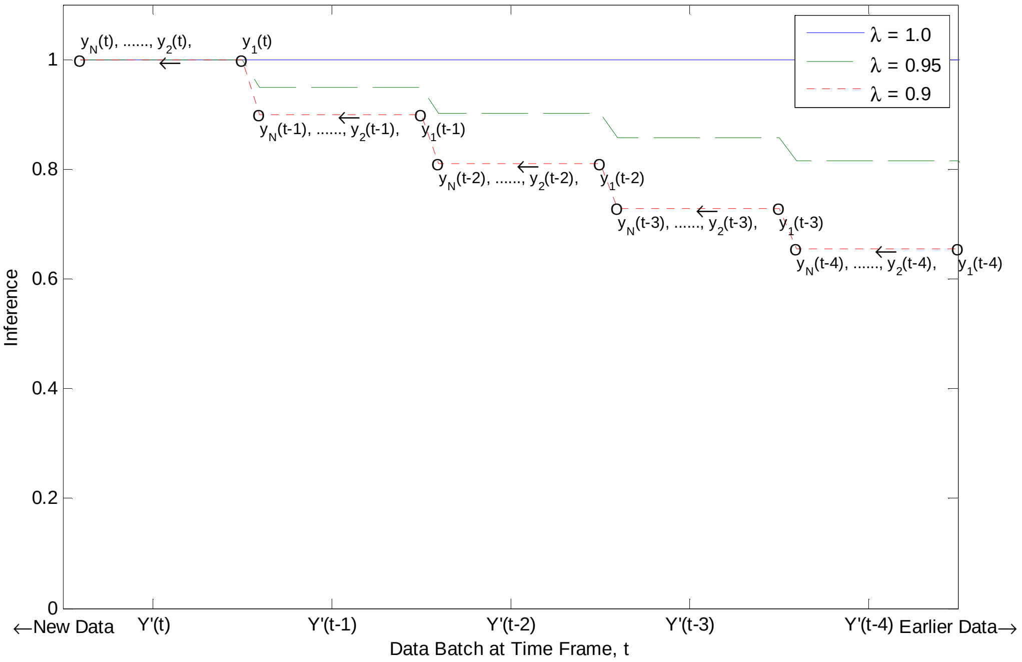


Figure 4.14 Decay of inference by the modified DENFIS

4.4 Design optimisation model

A design optimisation module is developed to determine the optimal design attribute settings of a product that can effectively draw the affection of target customers. GAs are introduced in this research to solve this design optimisation problem. Developing GA objective functions is important for obtaining the fitness values of GA population. Previous studies on affective design adopted either rule-based or model-based approaches to develop GA objective functions. In this research, a design optimisation model is proposed to generate optimal design attributes settings using guided search GA; in which both the trained NF model and discovered rules are used to find the optimal solutions.

4.4.1 Guided search genetic algorithms for design optimisation

The proposed guided search GA involves the NF model for affective prediction and approximate rules for a guided search to determine the optimal design attribute settings of affective design. The architecture of the design optimisation model, based on the guided search GA approach, is shown in Figure 4.15. A GA-based optimisation unit is used to generate possible design attribute settings. Each chromosome represents the solution vector, χ_i, which contains the design attribute settings $[x_1, x_2, \ldots, x_J]_i$, where $i = 1,2, \ldots N_{pop}$, and N_{pop} denotes the number of chromosomes in the population. As mentioned in Section 4.3, a trained NF model can be generated using the dynamic NF approach. The model is employed to predict customer affection based on the design attribute settings. The output of the NF model, $y(\chi_i)$, represents the predicted customer affection for solution vector χ_i, with a value between 0 and 1. The goal is to find the best design solution, χ_{Opt}, with its predicted affection close to the target side of the bipolar SD scale. The objective function is to minimise $[y(\chi_i)]$ if the target side is zero or to minimise $[-y(\chi_i)]$ if the target side is one. Thus, the fitness value of the objective function, $Fit(\chi_i)$, is the-smaller-the-better.

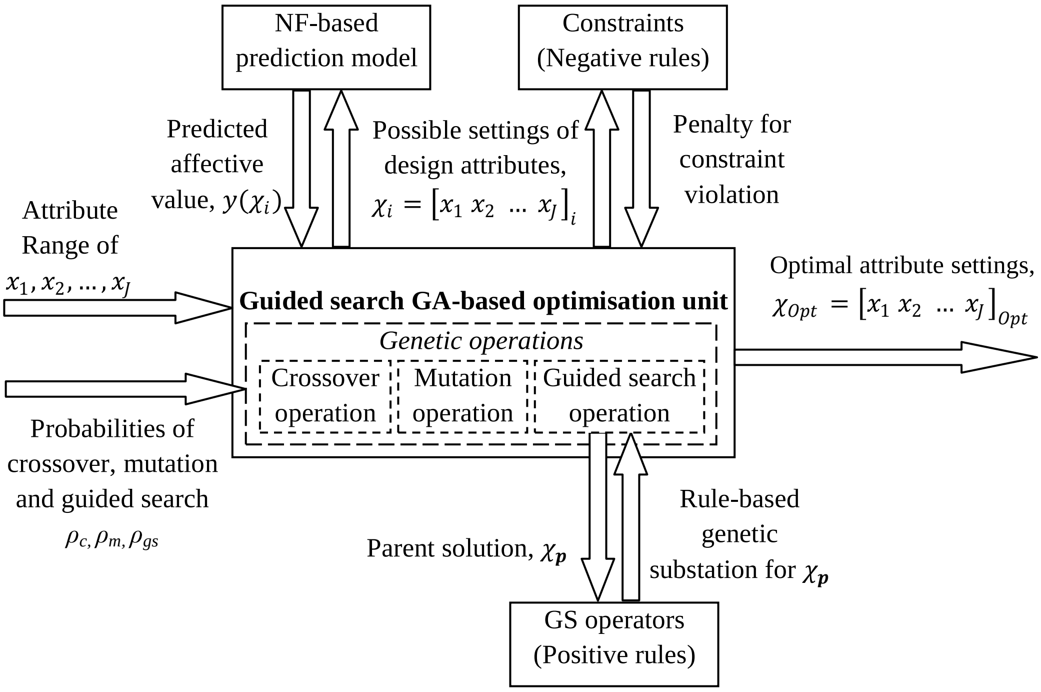

NF-based prediction model
Constraints (Negative rules)
Predicted affective value, $y(\chi_i)$
Possible settings of design attributes, $\chi_i = [x_1\ x_2\ \dots\ x_J]_i$
Penalty for constraint violation
Attribute Range of $x_1, x_2, \dots, x_J$
Guided search GA-based optimisation unit
Genetic operations
Crossover operation
Mutation operation
Guided search operation
Optimal attribute settings, $\chi_{Opt} = [x_1\ x_2\ \dots\ x_J]_{Opt}$
Probabilities of crossover, mutation and guided search $\rho_{c,}\rho_{m,}\rho_{gs}$
Parent solution, $\chi_{\boldsymbol{p}}$
Rule-based genetic substation for $\chi_{\boldsymbol{p}}$
GS operators (Positive rules)

Figure 4.15 Architecture of the guided search GA-based design optimisation model

A guided search strategy is proposed for the better application of prior knowledge to the design optimisation problem; which makes use of mined rules or a set of approximate rules generated by the MOGA-based rule-mining model. The approximate rules are divided into two subsets, namely, positive rules and negative rules. Positive rules are approximate rules with their approximate regions close to the target side of the SD scale. They describe attributes with the potential to invoke target customer affection. Negative rules are approximate rules with their approximate regions close to another side of the SD scale. They describe the undesirable attributes. When the objective function is set to minimise $[y(\chi_i)]$, approximate rules containing '$\psi \leq \psi_L$' in the rule consequence are positive rules, and those containing '$\psi \geq \psi_L$' are negative rules. When the objective function is set to minimise $[-y(\chi_i)]$, positive and negative rules are configured contrariwise. Different approaches are available for positive and negative rules.

A new genetic operator called guided search (GS) operator is introduced in this research to modify chromosomes and crossover and mutation operators for genetic operations. Crossover, mutation, and GS operators are randomly selected to generate children chromosomes during the GA reproduction process. ρ_c, ρ_m, and ρ_{gs} are the probabilities of performing crossover, mutation, and GS operators, respectively. Jat and Yang (2011) developed a GA guided search strategy for solving timetabling problem and more effectively arranging time slots of courses. They developed the GA that modifies a timetable solution using some pre-defined data structures as GS operators, such as moving and swapping time slots of consecutive events. The GS operators are executed when solutions violate any constraint. In the present research, positive rules indicate the range of attributes with a higher potential to invoke target customer affection. The GS operators are instructions for substituting the value of attributes described as positive rules. Therefore, the preferred range of attributes has more chances of being present in the population, such that the searching direction can be guided, and optimal design solutions can be found effectively. The detailed design of the GS operator is described in Section 4.4.4.

A penalty-based constraint approach is adopted to deal with the negative rules. Negative rules are translated as constraints to inhibit the selection of undesirable solutions from the GA population. Penalty methods are the most popular approach for handling constraints in GA because they are simple and easy to implement (Kalyanmoy, 2000). Jat and Yang (2011) demonstrated the guided search GA to deal with two kinds of constraints, namely, hard and soft constraints. Hard constraints deal with requirements that must not be violated and reject infeasible solutions. Soft constraints consider conditions that are less important but should preferably be satisfied. Soft constraint violations are measured using a penalty approach to sort the preference of candidate solutions. Jiao *et al.* (2007) proposed a GA using rule-based constraints to solve the product portfolio planning problem. Constraints are described as association rules that prevent infeasible associations between attributes generated during a GA-based search for optimal product attribute settings. A chromosome that violates the constraints is penalised in the population. The algorithm of the penalty-based constraint handling of the guided search GA is described in Section 4.4.5.

Candidate solutions are classified as desirable and undesirable solutions based on constraint violations. Each generation is sorted and selected according to fitness value, number of violated constraint, and penalties of constraint violations in the population. The ranking and selection processes of guided search GA are described in Section 4.4.6.

4.4.2 Chromosome design

A combined chromosome structure is used to deal with categorical and quantitative design attributes. For the categorical attributes, an integer-code genome is employed to represent the selected categorical option within an attribute domain. The range of the integer-code gene is from 1 to L_p if the categorical attribute A_p contains L_p items. For quantitative attributes, a real-coded gene is applied to deal with the continuous value. The search range of qth quantitative attribute is limited between $[v_q^{min}, v_q^{max}]$, where v_q^{min} and v_q^{max} are the minimum and maximum values of the qth quantitative attribute, respectively, of the training data sets for training the dynamic NF model. The chromosome design for the design optimisation process is illustrated in Figure 4.16.

Attribute Type	Categorical Attributes			Quantitative Attributes		
Attributes	A_p (x_1)	... ...	A_P (x_P)	A_q (x_{P+1})	... ...	A_Q (x_{P+Q})
Code type	Integer	Integer	Integer	Real number	Real number	Real number
Range	$[1, L_p]$	...	$[1, L_P]$	$[v_q^{min}, v_q^{max}]$	...	$[v_Q^{min}, v_Q^{max}]$

Figure 4.16 Combined chromosome structure for the design optimisation process

4.4.3 Initialisation, crossover, and mutation operators

The initialisation process is performed at the start of the GA run to generate an initial population based on population size. The diversity of initial population is important for a global optimum search. The initial values of categorical and quantitative attributes are randomly generated within their corresponding ranges, generating a diverse population.

Crossover and mutation operations are vital steps of GAs. Two sets of crossover and mutation operators are employed to deal with categorical and quantitative attributes encoded as integer-coded and real-coded genes, respectively. For integer-coded categorical attributes, a two-point crossover operator is employed to swap genes of two parent chromosomes between two random points and reproduce child chromosomes, as shown in Figure 4.17. The mutation operator for integer-coded categorical attributes is developed to randomly replace some points of a parent chromosome with new random numbers, as shown in Figure 4.18. For quantitative attributes, real-coded genes are copied with the simulated binary crossover and polynomial mutation introduced in Section 4.2.5 (Agrawal *et al*., 1995; Deb *et al*., 2002).

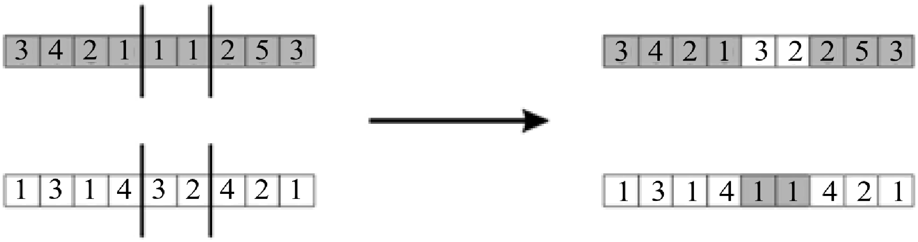


Figure 4.17 Two-point crossover operator for the integer-coded gene

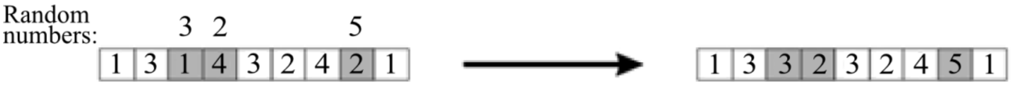


Figure 4.18 Mutation operator for the integer-coded gene

4.4.4 Penalty-based constraint handling

In the guide search GA, only negative rules in a rule set are used to formulate constraints. During the objective function evaluation of each chromosome, constraint violation is checked whether the number of violated constraints, $N_{vio}(\chi_i)$, is greater than zero. A constraint is violated if the attribute settings described in a chromosome match with the 'IF-part' of the corresponding rule.

For the $\text{n}th$ constraint formulated based on the corresponding negative rule R_{n}^{-}, its penalty value is formulated as follows:

$$Pen_{\text{п}}(\chi_i) = \begin{cases} w_{(R_{\text{п}}^-)} \times CF_{(R_{\text{п}}^-)} \times \left| \left(\dfrac{\psi_{L(R_{\text{п}}^-)}}{\psi_{max} - \psi_{min}} \right) - y(\chi_i) \right|, & \text{if } \chi_i \text{ violate пth constraint} \\ 0, & \text{if not} \end{cases} \tag{29}$$

where $w_{(R_{\text{п}}^-)}$ and $CF_{(R_{\text{п}}^-)}$ are the weight and confidence factor of rule $R_{\text{п}}^-$, respectively, $\psi_{L(R_{\text{п}}^-)}$ is the affective level described in the 'THEN-part' of rule *R*, and ψ_{min} and ψ_{max} are the minimum and maximum of affective levels based on the rating scale, respectively (Section 4.2.2).

Thus, the sum of penalties is calculated as follows:

$$Pen_{sum}(\chi_i) = \sum_{\text{п}=1}^{N_{con}} Pen_{\text{п}}(\chi_i) \tag{30}$$

where $\text{п} = 1,2, \dots, N_{con}$, and N_{con} is the number of constraints formulated.

4.4.5 Guided search operation

In each generation, a fraction of population is selected to perform a GS operation under a user-defined probability as well as crossover and mutation operations. The probability of performing a GS operation should not be greater than that of a mutation operation, i.e., $\rho_{gs} \le \rho_m$. Otherwise, population diversity is difficult to maintain. Only positive rules in the rule set are adopted for formulating guided search operators. Preferred attribute values are stated in the 'IF-part' of the positive rule. By substituting these values, there is a greater chance of finding a better and preferable solution. When parent solution, $\chi_{\boldsymbol{p}}$, is chosen to receive the GS operation, a child solution, $\chi_{\boldsymbol{c,g}}$, for $g = 1,2,\ldots,N_{gs}$, is generated by each GS operator, where N_{gs} is the number of GS operators. The attribute values of $\chi_{\boldsymbol{p}}$ are replaced, as described by the 'IF-part' of the rule. For categorical attributes, integer-code genes are replaced, as shown in Figure 4.19.

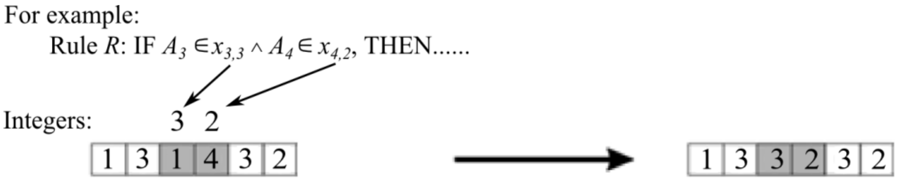

For example:
Rule R: IF $A_3 \in x_{3,3} \wedge A_4 \in x_{4,2}$, THEN......
Integers: 3 2
1 3 1 4 3 2
1 3 3 2 3 2

Figure 4.19 Guided search operator for the integer-coded gene

For quantitative attributes, a new value is randomly selected between the range $[v_q^{min}, v_q^{max}]$, as described by the rule for the qth quantitative attribute, and if qth quantitative attribute is included in the 'IF-part' of the rule. The new value of the qth quantitative attribute can be computed as follows:

$$x_{P+q} = \gamma_q \times \left(v_q^{max} - v_q^{min} \right) + v_q^{min} \tag{31}$$

where γ_q donates a random number generated between [0, 1].

The algorithm of the GS operation is shown in Figure 4.20. After each child solution is reproduced, its fitness value, $Fit(\chi_{\boldsymbol{c,g}})$, is evaluated, and the constraint violation and its penalty are found. Finally, the best child, χ_c^{best}, of the child solutions is found by ranking them according to their constraint violation, penalty, and fitness value. The substitution is withdrawn if the fitness value cannot be improved by the guided search operation; i.e., $Fit(\chi_c^{best})$ is worse than $Fit(\chi_{\boldsymbol{p}})$.

```
Randomly select one $\chi_i$ in the population as parent solution, $\chi_{\boldsymbol{p}}$
FOR $g$ = 1 to $N_{gs}$ // where $N_{gs}$ is the number of GS operators formulated
    Reproduce $\chi_{\boldsymbol{p}}$ as child solution $\chi_{\boldsymbol{c,g}}$ using $g$th GS operator
    Evaluate the fittest of objective function, $Fit(\chi_{\boldsymbol{c,g}})$, for solution $\chi_{\boldsymbol{c,g}}$
    IF solution $\chi_{\boldsymbol{c,g}}$ violates any constraints,
        Find $N_{vio}\left(\chi_{\boldsymbol{c,g}}\right)$
        Calculate $Pen_{sum}\,(\chi_i)$
    END IF
END FOR
Rank all children based on smaller {$N_{vio}\left(\chi_{\boldsymbol{c,g}}\right)$, $Pen_{sum}\,(\chi_i)$, $Fit(\chi_{\boldsymbol{c,g}})$}
Choose child ranked first as the best child $\chi_c^{best}$
// compare the fittest of objective function between the best child and parent
IF $Fit(\chi_c^{best}) < Fit(\chi_{\boldsymbol{p}})$,
    // return the best child if $\chi_c^{best}$ is better than $\chi_{\boldsymbol{p}}$
    RETURN $\chi_c^{best}$
ELSE
    RETURN $\chi_{\boldsymbol{p}}$
END IF
```

Figure 4.20 Pseudo-code of the guided search operation

4.4.6 Ranking and selection of the next generation

Three criteria are addressed in the ranking process: $Fit(\chi_i)$, $N_{vio}(\chi_i)$, and $Pen_{sum}(\chi_i)$. Population can be classified into two groups, namely, undesirable and not undesirable. Candidate solutions are not undesirable if they do not have constraint violations; i.e., $N_{vio}(\chi_i) = 0$. Solutions are normally ranked according to their fitness value $Fit(\chi_i)$.

They all dominate the undesirable solutions. For candidate solutions that violate any constraint $N_{vio}(\chi_i) \geq 1$, their priorities are based on parameters, $N_{vio}(\chi_i)$ and $Pen_{sum}(\chi_i)$. Let χ_1 and χ_2 be two different solution vectors. χ_1 dominates χ_2 if $N_{vio}(\chi_1) < N_{vio}(\chi_2)$. If $N_{vio}(\chi_1) = N_{vio}(\chi_2)$, the sum of penalties of χ_1 and χ_2 is compared; χ_1 dominates χ_2 if $Pen_{sum}(\chi_1) < Pen_{sum}(\chi_2)$.

For each generation, the pool of chromosomes is formed by recombining the current population (parents) and the reproduced children. Child chromosomes are generated until the pool size is equal to $N_{pop} \times 2$. The selection process is performed after the preparation of the pool of chromosomes. Binary tournament selection method is adopted for the guided search GA. The binary tournament selection method is an effective selection operator of GAs (Deb *et al.*, 2002). Two solutions are randomly selected from the pool of chromosomes, and the better one is selected as the offspring of the next generation. The binary tournament selection is repeated until the population size of the new generation reaches N_{pop}. Figure 4.21 presents the flowchart of the guided search GA.

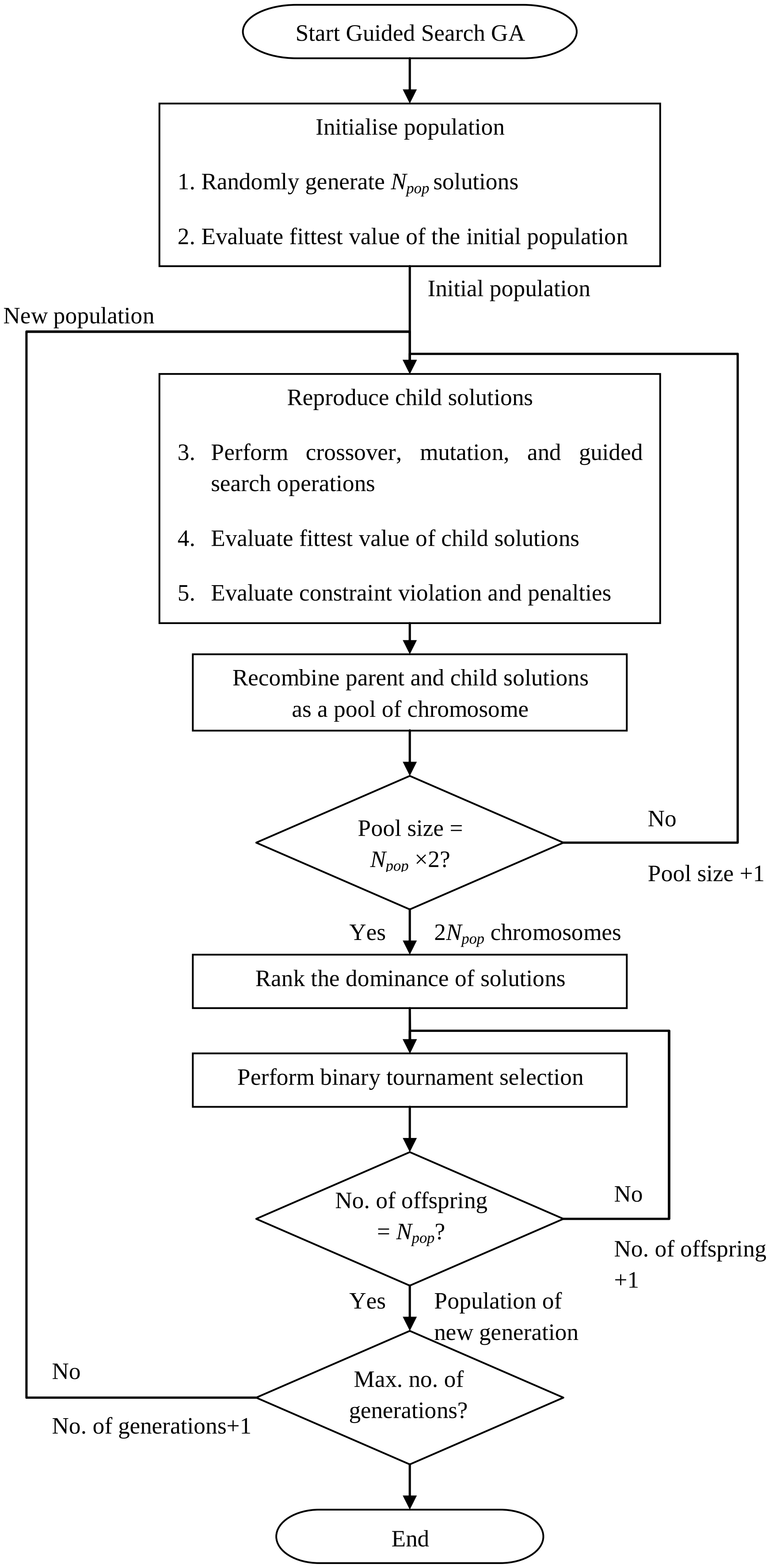

Start Guided Search GA
Initialise population
1. Randomly generate N_{pop} solutions
2. Evaluate fittest value of the initial population
Initial population
New population
Reproduce child solutions
3. Perform crossover, mutation, and guided search operations
4. Evaluate fittest value of child solutions
5. Evaluate constraint violation and penalties
Recombine parent and child solutions as a pool of chromosome
Pool size = N_{pop} ×2?
No
Pool size +1
Yes
$2N_{pop}$ chromosomes
Rank the dominance of solutions
Perform binary tournament selection
No. of offspring = N_{pop}?
No
No. of offspring +1
Yes
Population of new generation
No
Max. no. of generations?
No. of generations+1
End

Figure 4.21 Flowchart of the guided search GA

Chapter 5 Implementation and Results

In this chapter, a case study of the product form design for mobile phones is used to investigate the effectiveness of the proposed methodology and the intelligent system to support affective design.

The case study mainly involves a survey and the implementation of an intelligent system of affective design for mobile phones. The survey was conducted using questionnaires, and the intelligent system was implemented using the MATLAB software programming language.

5.1 Case study of affective design for mobile phones

A survey was conducted using questionnaires to gather customer affections on 32 mobile phone samples based on four product images: simplicity, uniqueness, high tech, and handiness. Figure 5.1 shows the front and side views of the 32 mobile phone samples. A total of 34 respondents filled out the questionnaires and indicated their feelings towards the product images of each sample using a five-point Likert scale. The survey questionnaires are presented in Appendix A.

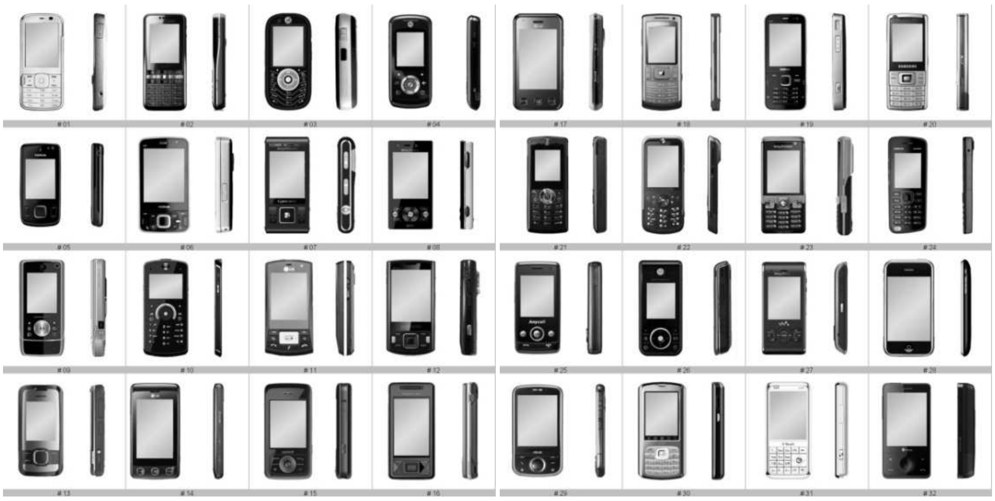


Figure 5.1 The 32 mobile phone samples used in the case study

The morphological approach was adopted to define the design space of the product form of mobile phones. Depicting the design composition and possible design solutions with simple and graphical notations was feasible. Eight design attributes were defined to describe the product forms of mobile phones, including top shape, bottom shape, function button shape, layout, length, width ratio, thickness, and border width. The first four attributes are categorical, and the remaining four attributes are quantitative. The categorical attributes contain three to five options. The attributes and their options are listed in a design table for the product form of the mobile phones, as shown in Table 5.1. Based on the design table, the design profile for each sample was identified, and the values of attributes were measured. The obtained design data of the 32 mobile phone samples are shown in Table 5.2.

Table 5.1 Design table for the product form of the mobile phones

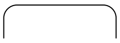
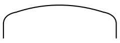
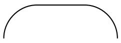
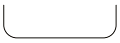
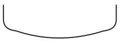
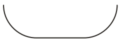
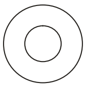
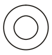
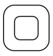
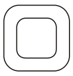
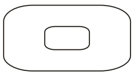
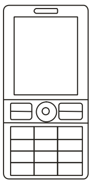
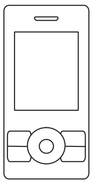
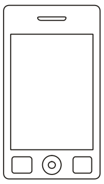
Categorical Attributes						
	Elements	**Type 1**	**Type 2**	**Type 3**	**Type 4**	**Type 5**
1.	Top Shape (A_1)	 Line (x_{11})	 Arc (x_{12})	 Curve (x_{13})		
2.	Bottom Shape (A_2)	 Line (x_{21})	 Arc (x_{22})	 Curve (x_{23})		
3.	Function Button Shape (A_3)	 Large round (x_{31})	 Small round (x_{32})	 Small squares (x_{33})	 Large square (x_{34})	 Wide Block (x_{35})
4.	Layout (A_4)	 Bar (x_{41})	 Slide (x_{42})	 Large screen (x_{43})		
Quantitative Attributes						
5.	Body Length (A_5)					
6.	Body Width (A_6)					
7.	Body Thickness (A_7)					
8.	Border Width (A_8)					

Table 5.2 Design data of the 32 mobile phone samples

Sample No.	**Top Shape (A_1)**	**Bottom Shape (A_2)**	**Function Button (A_3)**	**Layout (A_4)**	**Body Length, mm (A_5)**	**Body Width, mm (A_6)**	**Body Thick, mm (A_7)**	**Border Width, mm (A_8)**
1	$x_{1,1}$	$x_{2,1}$	$x_{3,4}$	$x_{4,1}$	100	49	14	2.1
2	$x_{1,1}$	$x_{2,1}$	$x_{3,3}$	$x_{4,1}$	102	48	14	2.3
3	$x_{1,3}$	$x_{2,3}$	$x_{3,1}$	$x_{4,1}$	89	52	23	3.3
4	$x_{1,2}$	$x_{2,2}$	$x_{3,1}$	$x_{4,2}$	87	46	14	3.2
5	$x_{1,1}$	$x_{2,2}$	$x_{3,4}$	$x_{4,2}$	71	44	13	5.7
6	$x_{1,1}$	$x_{2,1}$	$x_{3,4}$	$x_{4,2}$	95	54	18	1.8
7	$x_{1,1}$	$x_{2,1}$	$x_{3,4}$	$x_{4,2}$	104	49	19	0.9
8	$x_{1,1}$	$x_{2,1}$	$x_{3,2}$	$x_{4,2}$	94	47	13	1.0
9	$x_{1,1}$	$x_{2,2}$	$x_{3,1}$	$x_{4,2}$	86	50	17	4.0
10	$x_{1,2}$	$x_{2,2}$	$x_{3,1}$	$x_{4,1}$	104	52	9	1.3
11	$x_{1,2}$	$x_{2,2}$	$x_{3,5}$	$x_{4,2}$	108	54	21	4.5
12	$x_{1,2}$	$x_{2,2}$	$x_{3,4}$	$x_{4,2}$	98	53	21	4.0
13	$x_{1,3}$	$x_{2,3}$	$x_{3,4}$	$x_{4,2}$	89	48	15	4.2
14	$x_{1,2}$	$x_{2,2}$	$x_{3,3}$	$x_{4,3}$	99	54	11	2.1
15	$x_{1,2}$	$x_{2,1}$	$x_{3,1}$	$x_{4,2}$	101	53	18	1.8
16	$x_{1,1}$	$x_{2,1}$	$x_{3,5}$	$x_{4,2}$	104	52	17	2.2
17	$x_{1,1}$	$x_{2,1}$	$x_{3,3}$	$x_{4,3}$	99	55	17	3.2
18	$x_{1,2}$	$x_{2,2}$	$x_{3,5}$	$x_{4,1}$	104	45	11	3.2
19	$x_{1,1}$	$x_{2,1}$	$x_{3,4}$	$x_{4,1}$	103	45	17	1.4
20	$x_{1,2}$	$x_{2,2}$	$x_{3,5}$	$x_{4,1}$	103	45	13	2.5
21	$x_{1,2}$	$x_{2,2}$	$x_{3,1}$	$x_{4,1}$	104	46	16	1.3
22	$x_{1,3}$	$x_{2,2}$	$x_{3,1}$	$x_{4,1}$	104	50	13	1.8
23	$x_{1,1}$	$x_{2,1}$	$x_{3,2}$	$x_{4,1}$	101	48	17	2.1
24	$x_{1,2}$	$x_{2,2}$	$x_{3,4}$	$x_{4,1}$	98	43	11	1.6
25	$x_{1,2}$	$x_{2,2}$	$x_{3,4}$	$x_{4,2}$	92	48	16	2.0
26	$x_{1,1}$	$x_{2,3}$	$x_{3,1}$	$x_{4,2}$	94	47	19	3.3
27	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	$x_{4,2}$	94	47	13	1.6
28	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	$x_{4,3}$	99	57	11	2.8
29	$x_{1,2}$	$x_{2,2}$	$x_{3,2}$	$x_{4,2}$	88	54	10	3.3
30	$x_{1,2}$	$x_{2,2}$	$x_{3,1}$	$x_{4,1}$	103	55	14	3.8
31	$x_{1,1}$	$x_{2,1}$	$x_{3,5}$	$x_{4,1}$	107	55	16	4.6
32	$x_{1,1}$	$x_{2,1}$	$x_{3,2}$	$x_{4,2}$	95	51	19	1.1

5.2 Implementation of the MOGA-based rule-mining model

The proposed rule-mining approach was implemented to discover the design rules for the affective dimension ‘handiness’. The proposed rule involves two stages. At the first stage of rule mining, population size and generations were set to 30 and 1,000, respectively. Crossovers and mutations used in the NSGA-II were set to 80% and 20%, respectively. At the second stage, population size was set to 50 to search for an optimal rule set. The initial population of the chromosomes representing the candidate rule set solution was compiled based on the mined rules from the first stage. Each rule of the rule set was assigned with a weight initialised with a random number drawn between [0, 1]. The rule-filtering threshold was set to 0.8. The NSGA-II-based rule mining was run for 500 generations to ascertain the convergence of the MOGA model.

K-fold and leave-one-out cross-validation tests are often used to evaluate the generalisation errors of prediction models. *K*-fold cross-validation divides a data set into *k*-subsets and repeat training process for *k*-times with replacing the training and test sets. Leave-one-out cross-validation is similar to *k*-fold cross-validation but *k* is equal to the sample size. Each sample must act as a test sample in one trial and the other samples are used to be a training set. Therefore, the generalisation error of a model can be validated by analysing the errors obtained from the cross-validation tests. K-fold cross-validation was chosen in this study as leave-one-out cross-validation performs quite poorly for classification of discontinuous data (Priddy and Keller, 2005).

The overall performance of the MOGA-based rule-mining method was examined using an eight-fold cross-validation test. The 32 mobile phone samples were categorised into training and test sets. For each fold, 28 samples were used for training, and the remaining four samples were reserved for an unknown set to test the generalisation of discovered rules. A prototype of the MOGA-based rule-mining model of the proposed intelligent system was implemented using the MATLAB software programming language. The following section describes one rule set generated from the prototype of the rule-mining model. The performance of the MOGA-based rule-mining method is discussed in Section 5.2.2.

5.2.1 Generated rule sets

The validation of rule set related to ‘handiness’ generated by the MOGA-based rule-mining model is described in this section. The rule set resulted from one of the eight-fold cross-validation tests shown in Table 5.3, in which nine approximate rules are generated. The rules $R_1 - R_6$ are positive rules for ‘handiness’, and they identify the design patterns likely to induce a handy design. For example, a design contains the design pattern described in R_1 that possibly feels ‘very handy’ or at worst ‘handy’. The rules $R_7 - R_9$ are negative rules for ‘handiness’. A pattern described in a negative rule leads to a bulky design, and it probably cannot induce any ‘very handy’ design. For example, R_8 states that the induced customer affection is ‘very bulky’, or at most ‘normal’, if thickness (A_7) is greater than 16 mm (as 23 mm is the maximum value of the pre-defined range of thickness).

Knowledge can be obtained by resolving the approximate rules for supporting affective design. The key design attributes and their relationships with customer affection can be investigated. For example, thickness (A_7**)** is a key design attribute because it appeared the most frequently in the entire rule set. Based on the rules that contains thickness (A_7), the relationship between thickness and ‘handiness’ can be visualised, as shown in Table 5.4. The interaction among the rules in the rule set is examined in Table 5.4. The overlapping of the rules reflects the ranges that may be more significant. Not surprisingly, diminishing thickness formed a design that seems handier and vice versa. It also helps users better understand the preferred and undesirable ranges of design attributes with regard to customer affection.

Rules R_2 and R_3 shown in Table 5.3 are similar and their attribute values are very close. Similar rules are less interesting to users in conventional rule-mining approaches because they lend to provide the same decision support information. Indeed, R_2 contains one more attribute compared with R_3. Therefore, R_2 is a more specialised rule and R_3 is a more generalised rule. Moreover, the confidence factor of R_2 is greater than that of R_3, i.e. $CF(_{R_2}) > CF(_{R_3})$. The similar rules create a finer partitioning of the data space for more accurate classification. Besides, rules R_2 and R_3 are relatively weak in the rule set. The weighted confidences of R_2 and R_3 are lower than those of the other rules of the rule set. Since the proposed rule-mining approach determines an aggregated decision by weighted voting based on the weighted confidence, similar weak rules work together to increase the confidence of an aggregated decision.

In the cross-validation test, the validity of a rule set was tested with a test sample set. For the rule set discussed above, their corresponding test samples and survey data statistical results are shown in Table 5.5. The design attribute settings of the test samples are presented in Table 5.2. The mean rating is the average raw rating, which is equal to the sum of the ratings divided by the number of respondents. Table 5.6 shows the design rules that match with the test samples, in which the rule conditions of the rules coincide with the design attribute settings of the test samples shown in Table 5.5. The aggregate decision of each test sample was voted according to the weighted confidence of the rules, and the approximate region was formed between the lower and upper limits.

Aggregate decisions of the four test samples were obtained based on the rule set shown in Table 5.6. For each test sample, the aggregate decision was tested by comparing it with the mean rating of the survey results. If the mean rating is within the approximate region of the aggregate decision, the result is considered a correct classification of the test sample using the rule set. Otherwise, the rule set fails to classify the test sample because a decision suggested by the rule set contradicts the mean value of the survey data. For sample No. 17, rules R_4 and R_8 match and vote for the upper and lower limits of the aggregate decision, respectively. The formed decision precisely classified this sample as $3 \leq \psi_{HA} \leq 3$ ('normal'). As the result was consistent with mean rating (equal to 3.0), sample No. 17 was correctly classified by the rule set. For sample No. 24, rules, R_3 and R_5, indicate the upper limits of ψ_{HA} as 2 and 3. The chosen rule R_5 formed the decision $\psi_{HA} \leq 3$ ('very handy' or at worst 'normal'), as the weighted confidence of R_5 was greater than R_3. Samples No. 28 and No. 32 only matched with a single rule, and their unspecified ends were substituted by default classes 'very handy' and 'very bulky', respectively.

Table 5.3 Rule set obtained using the MOGA-based rule-mining method

	Rule No.	**Rule Statements**	***CF*$_{(R)}$**	***w*$_{(R)}$**	***Def*(*R*)**
Finding upper limit (+ve *R*)	R_1	IF Bottom shape (A_2) $\in$ [$x_{2,2}$] $\wedge$ Width (A_6) $\in$ [51, 56] $\wedge$ Border (A_8) $\in$ [2, 2.6], THEN $\psi_H \leq 2$ [VH, H].	0.74	0.95	0.75
	R_2	IF Bottom shape (A_2) $\in$ [$x_{2,2}$] $\wedge$ Width (A_6) $\in$ [51, 56] $\wedge$ Thickness (A_7) $\in$ [9, 11], THEN $\psi_H \leq 2$ [VH, H].	0.65	0.87	0.75
	R_3	IF Bottom shape (A_2) $\in$ [$x_{2,2}$] $\wedge$ Thickness (A_7) $\in$ [9, 13], THEN $\psi_H \leq 2$ [VH, H].	0.5	0.88	0.75
	R_4	IF Button (A_3) $\in$ [$x_{3,3}$] $\wedge$ Layout (A_4) $\in$ [$x_{4,3}$] $\wedge$ Border (A_8) $\in$ [2, 5.2], THEN $\psi_H \leq$ 3 [VH, N].	0.94	1.0	0.5
	R_5	IF Thickness (A_7) $\in$ [9, 16], THEN $\psi_H \leq 3$ [VH, N].	0.79	0.99	0.5
	R_6	IF Thickness (A_7) $\in$ [13, 15], THEN $\psi_H \leq 4$ [VH, B].	0.96	0.92	0.25
Finding lower limit (-ve *R*)	R_7	IF Top (A_1) $\in$ [$x_{1,1}$] $\wedge$ Thickness (A_7) $\in$ [16, 17] $\wedge$ Border (A_8) $\in$ [2, 2.3], THEN $\psi_H \geq 2$ [H, VB].	0.99	0.84	0.25
	R_8	IF Thickness (A_7) $\in$ [16, 23], THEN $\psi_H \geq 3$ [N, VB].	0.76	0.83	0.5
	R_9	IF Thickness (A_7) $\in$ [20, 23], THEN $\psi_H \geq 4$ [B, VB].	0.44	0.91	0.75

where ψ_H is the rule approximation for handiness of mobile phones, VH is very handy (ψ_H=1), H is handy (ψ_H=2), N is normal (ψ_H=3), B is bulky (ψ_H=4), and VB is very bulky (ψ_H=5).

Table 5.4 Relationships between thickness and handiness found by the rule set

<table>
<tr><th>Thickness (A_7) /mm</th><th>9</th><th>…</th><th>11</th><th>…</th><th>13</th><th>…</th><th>15</th><th>16</th><th>17</th><th>…</th><th>…</th><th>20</th><th>…</th><th>…</th><th>23</th></tr>
<tr><td><b><i>Rule</i>2(+ve)</b></td><td colspan="3">$\Psi_H \le 2$ [VH, H] (<i>CF</i> = 0.65) ◄──►</td><td colspan="12"></td></tr>
<tr><td><b><i>Rule3</i>(+ve)</b></td><td colspan="5">$\Psi_H \le 2$ [VH, H] (<i>CF</i> = 0.5) ◄──►</td><td colspan="10"></td></tr>
<tr><td><b><i>Rule</i>5(+ve)</b></td><td colspan="8">$\Psi_H \le 3$ [VH, N] (<i>CF</i> = 0.79) ◄──►</td><td colspan="7"></td></tr>
<tr><td><b><i>Rule</i>6(+ve)</b></td><td colspan="4"></td><td colspan="3">$\Psi_H \le 4$ [VH, B] (<i>CF</i> = 0.96) ◄──►</td><td colspan="8"></td></tr>
<tr><td><b><i>Rule</i>7(-ve)</b></td><td colspan="7"></td><td colspan="2">$\Psi_H \ge 2$ [H, VB] (<i>CF</i> = 0.99) ◄──►</td><td colspan="6"></td></tr>
<tr><td><b><i>Rule</i>8(-ve)</b></td><td colspan="7"></td><td colspan="8">$\Psi_H \ge 3$ [N, VB] (<i>CF</i> = 0.76) ◄──►</td></tr>
<tr><td><b><i>Rule</i>9(-ve)</b></td><td colspan="11"></td><td colspan="4">$\Psi_H \ge 4$ [B, VB] (<i>CF</i> = 0.44) ◄──►</td></tr>
</table>

Table 5.5 Survey results of test samples in one of the cross-validation tests

Samples No. (test set)	**Design Attribute Settings (A_1-A_8)**								**Ratings (Frequency)**					**Mean Rating**
									VH	**H**	**N**	**B**	**VB**	
17	$x_{1,1}$	$x_{2,1}$	$x_{3,3}$	$x_{4,3}$	99	55	17	3.2	2	6	16	9	1	3.0
24	$x_{1,2}$	$x_{2,2}$	$x_{3,4}$	$x_{4,1}$	98	43	11	1.6	2	9	13	9	1	2.6
28	$x_{1,1}$	$x_{2,1}$	$x_{3,1}$	$x_{4,3}$	99	57	11	2.8	4	9	14	7	0	2.5
32	$x_{1,1}$	$x_{2,1}$	$x_{3,2}$	$x_{4,2}$	95	51	19	1.1	2	8	16	6	2	3.5

Table 5.6 Validity of rules for the test samples

Samples No. (test set)	**Rule Matched**		**Weighted confidence** $CF_{(R)} \times w_{(R)}$	**Aggregate Decision**	**Mean Rating**	**Mean Value Test**
17	R_4 *	IF Button (A_3) $\in [x_{3,3}] \wedge$ Layout (A_4) $\in [x_{4,3}] \wedge$ Border (A_8) $\in$ [2, 5.2], THEN $\psi_H \leq 3$ [VH, N].	0.94	$3 \leq \psi_{HA} \leq 3$ [N]	3.0	True
	R_8 #	IF Thickness (A_7) $\in$ [16, 23], THEN $\psi_H \geq 3$ [N, VB].	0.63			
24	R_3	IF Bottom shape (A_2) $\in [x_{2,2}] \wedge$ Thickness (A_7) $\in$ [9, 13], THEN $\psi_H \leq 2$ [VH, H].	0.44	$\psi_{HA} \leq 3$ [VH, N]	2.6	True
	R_5 *	IF Thickness (A_7) $\in$ [9, 16], THEN $\psi_H \leq 3$ [VH, N].	0.78			
28	R_5 *	IF Thickness (A_7) $\in$ [9, 16], THEN $\psi_H \leq 3$ [VH, N].	0.78	$\psi_{HA} \leq 3$ [VH, N]	2.5	True
32	R_8 #	IF Thickness (A_7) $\in$ [16, 23], THEN $\psi_H \geq 3$ [N, VB].	0.63	$\psi_{HA} \geq 3$ [N, VB]	3.5	True

where ψ_{HA} donates the aggregate decision for 'handiness'.

* represents the rule selected for the upper limits based on the weighted vote method
# represents the rule selected for the lower limits based on the weighted vote method

Figure 5.2 shows the Pareto front generated from the MOGA-based rule-mining model. The rule set is a trade-off solution selected from the Pareto front at the point where *Acc*(*S*) is about 0.80, *Cmplx*(*S*) is about 27, and *Def*(*S*) is about 0.46. Although the selected trade-off solution is slightly less accurate than the most accurate solution, its definability is relatively greater. The definability of the rule set is important for generating precise classification. The plot shows that the accuracy of the rule sets slightly increases when its complexity decreases to a suitable range of 20 to 25. The trend is possibly caused by overfitting to the training data as the rules contain too many or unnecessary attributes. However, accuracy significantly decreases when the complexity of the rule sets is smaller than the suitable range. If the number of rules in the rule set is too small, there may be insufficient rules to rationalise relationships in the entire data set. Apart from the relationship between accuracy and complexity, a remarkable trade-off exists between the accuracy and the definability of the solutions. The definability of the rule set, *Def*(*S*), was estimated from the average extent of approximate regions of the training set. Solutions obtained at the upper end of the Pareto front have greater definability, but their accuracy is low. In contrast, the most accurate solution was obtained at the lower edge of the Pareto front. However, its definability dropped, and the decisions obtained from the rule set were imprecise. Users can choose from the rule set solution according to their needs and priorities of accuracy, complexity, and definability. In the present study, solutions are considered vague and imprecise if *Def*(*S*) is smaller than 0.4.

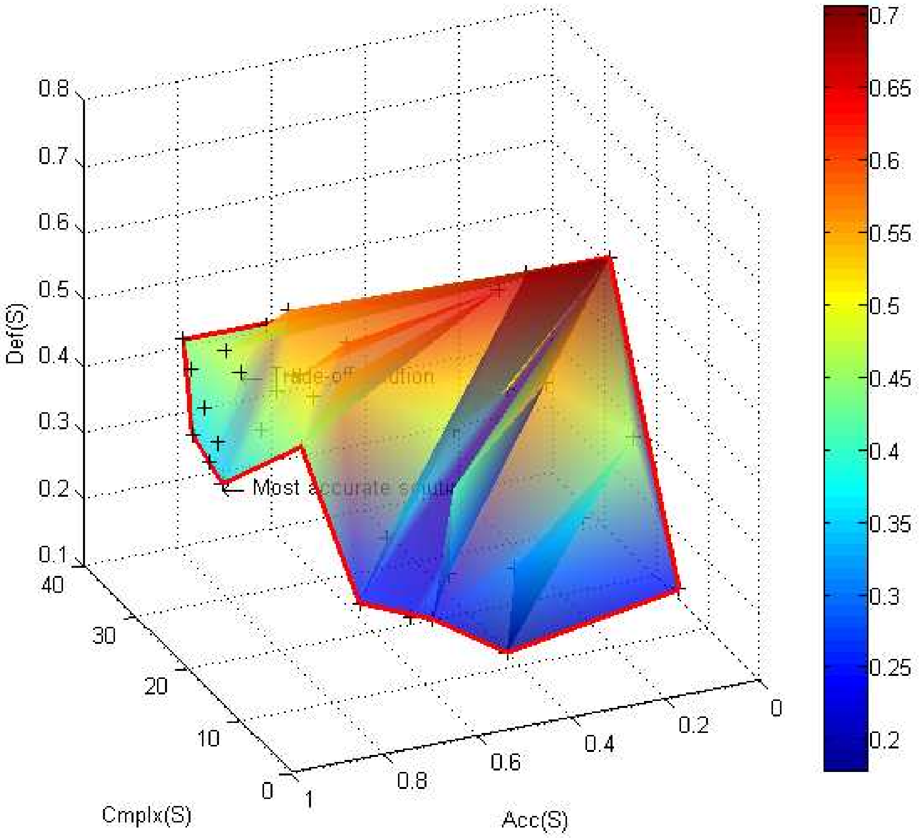


Figure 5.2 Pareto front of the MOGA-based rule mining

5.2.2 Performance of the MOGA-based rule mining

The mean value test results of the eight-fold cross-validation tests are shown in Table 5.7. The proposed method can discover the approximate rule set with an overall support rate of 93.75%. As the sample size is small, and the outliers probably exist in the survey data, the overall accuracy is considered acceptable.

As approximate rules were generated in this study, the definability of the rule sets was introduced to estimate the extent of approximation. A rule set has good definability if it can precisely classify examples and if its approximation is less rough.

Table 5.8 presents the definability of the aggregate decisions for the test samples obtained based on the mined rule sets. Most test samples were roughly classified as vague approximations, where $Def(\psi_{\boldsymbol{HA}}) < 1$. Only one test sample from the first fold of the cross-validation test was classified definitely as crisp decisions, where $Def(\psi_{\boldsymbol{HA}}) = 1$. Results with $Def(\psi_{\boldsymbol{HA}})$ = 0.5 accounted for nearly 60% of the test cases. Inconsistencies existed in the ratings evaluated by different respondents for the same product sample. Usually, human subjects assign ratings around the mean ± one point or one standard deviation away from the mean, which may support why the results with $Def(\psi_{\boldsymbol{HA}})$ > 0.5 are rare cases. Increasing the number of points in the rating scale may improve the definability associated with these cases. The results with $Def(\psi_{\boldsymbol{HA}}) \leq 0.25$ are undesirable cases because the classifications of these cases are highly vague and not well classified. These cases are not very useful in determining the relationships between design attributes and customer affections. Larger counts of cases with lower definability indicate greater ambiguity and inconsistency in the survey data. Traditional rule-mining methods may not be able to deal with the highly vague customer affections accurately using crisp rules. The proposed rule-mining model can better consider the inconsistency and vagueness of the survey data using approximate rules.

Table 5.7 Results of the mean value test of eight-fold cross-validation tests

Fold	**Number of Decisions on Test Samples**	
	Pass Mean Value Test	**Fail Mean Value Test**
1	4	0
2	4	0
3	4	0
4	4	0
5	4	0
6	3	1
7	4	0
8	3	1
Overall	**30 (93.75%)**	**2 (6.25%)**

Table 5.8 Definability of the rule set decision on the test sample set

Fold	**Frequency of**			
	$\boldsymbol{Def(\psi_{HA})=1}$	$\boldsymbol{Def(\psi_{HA})=0.75}$	$\boldsymbol{Def(\psi_{HA})=0.5}$	$\boldsymbol{Def(\psi_{HA})=0.25}$
1	1	0	3	0
2	0	0	2	2
3	0	1	2	1
4	0	0	4	0
5	0	1	2	1
6	0	0	2	2
7	0	0	3	1
8	0	3	1	0
Overall	**1 (3.13%)**	**5 (15.63%)**	**19 (59.38%)**	**7 (21.88%)**

The proposed MOGA-based rule-mining method is validated by comparing its mining results with those based on the DRS-based rule-mining method (Zhai *et al*., 2009b). The DRS approach is applied to mine rules from the entire set of affective design data and implemented as a rule-based decision support system called 4kMka (Greco *et al*., 2002). The rules generated by the DRS approach are shown in Table 5.9. Based on the table, three out of five rules achieve 33% confidence only. The fifth rule is a useless classification rule because its *Def*(*R*) is equal to zero. The fourth rule extracted by the DRS-based rule-mining approach is similar to rule R_4 generated by the proposed rule-mining approach. However, the latter has greater confidence and better definability than the former. From the view of mining individual rules, the DRS-based rule-mining approach generates rules with more errors and worse quality than those generated based on the proposed rule-mining approach.

An overall performance comparison between the proposed rule-mining and DRS-based rule-mining approach is shown in Table 5.10. There are three criteria of rule quality, namely, average confidence of rules, average definability of rules, and comprehensibility of the entire rule set. All three estimators range between [0, 1], and they are known as the greater-is-better. Both average confidence and average definability of rules generated by the proposed rule-mining approach are greater than those generated based on the DRS-based rule-mining approach. The results indicate that the proposed rule-mining approach outperforms the DRS-based rule-mining in generating rule sets with higher accuracy and reliability, and better definability. However, the rule set generated by the proposed rule-mining approach is less comprehensible than that generated based on the DRS-based rule-mining approach. If the number of rules is too large, the interactions among the rules become more complex. This shortcoming can reduce the comprehensibility and interestingness of the rule set, and users may find understanding and utilising the rule set difficult. However, the rule set has nine rules only, and it is considered acceptable in this study. Table 5.11 presents a comparison of test results between the proposed rule-mining and DRS-based rule-mining approaches for the four affective data sets. From the table, it can be seen that the proposed rule-mining approach has higher accuracy for all the data sets, and better robustness than the DRS-based rule-mining approach.

Table 5.9 Rule set obtained based on the DRS-based rule-mining approach

Rule No.	**Rule Statements**	***CF*$_{(R)}$**	***Def*(*R*)**

1	IF Layout (A_4) ∊ [$x_{4,2}$ or $x_{4,3}$ or x_{45}] ∧ Length (A_5) ≥ 101 ∧ Border (A_8) ≤ 2.1,
	THEN $\psi_H \geq 2$ [H, VB]
		1.00	0.25

2	IF Thickness (A_7) ≤ 0.9,
	THEN $\psi_H \leq 4$ [VH, B]
		0.33	0.25

3	IF Border (A_8) ≥ 5.7,
	THEN $\psi_H \leq 4$ [VH, B]
		0.33	0.25

4	IF Button (A_3) ∊ [$x_{3,3}$] ∧ Border (A_8) ≥ 4.2 ,
	THEN $\psi_H \leq 4$ [VH, B]
		0.33	0.25

5	IF Thickness (A_7) ≤ 5.7,
	THEN $\psi_H \leq 5$ [VH, VB]
		1.00	0

Table 5.10 Comparison between the proposed and the DRS-based rule-mining approaches

	Proposed Rule-mining	**DRS-based Rule-mining**
Number of rules generated	9	5
Average $Conf(R)$	0.75	0.60
Average $Def(R)$	0.556	0.2
$Comp(S)$	0.0385	0.0667

Table 5.11 Test results of the proposed and the DRS-based rule-mining approaches for various data sets

Affective Data Set	**Average Accuracy of**	
	Proposed Rule-mining	**DRS-based Rule-mining**
Simplicity	84.375%	84.375%
Uniqueness	84.375%	68.75%
High tech	90.625%	59.375%
Handiness	93.75%	56.25%

5.3 Implementation of the dynamic NF model

A dynamic NF model for modelling affective relationships was developed by obtaining survey data sets from the first five respondents in the initialisation of the dynamic NF model. Then, the data sets of the others were sequentially trained batch by batch for the recursive update of the dynamic NF model. The forgetting factor λ = 0.95 was set to produce a slight decay of inference. Two dynamic NF models, with and without BP training, were tested. The dynamic NF models were implemented using the MATLAB software programming language.

5.3.1 Generated dynamic NF model

The structure of the dynamic NF model was generated based on the proposed dynamic NF model, as shown in Figure 5.5. Five rule nodes represented the local models formulated based on clustering using ECM. For each input attribute, five MFs were linked to separate rule nodes. The set of TSK fuzzy rule-based models was generated, as shown in Figure 5.3. Each fuzzy rule contained a local model. Its effective domain was governed by fuzzy MFs of the design attributes, as shown in Figure 5.4. The resulting local models were aggregated to determine customer affection on a new design for mobile phones after inputting the design attribute settings of mobile phones.

Model 1:

If x_1 is MF_{12} *and* x_2 is MF_{21} *and* x_3 is MF_{31} *and* x_4 is MF_{41} *and* x_5 is MF_{51} *and* x_6 is MF_{63} *and* x_7 is MF_{72} *and* x_8 is MF_{83}, *Then* y_H = (0.7832- 0.3457x_1 + 0.4648x_2 - 0.0777x_3, -0.1483x_4 - 0.5625x_5 + 0.1666x_6 + 0.1792x_7 - 0.4252x_8).

Model 2:

If x_1 is MF_{15} *and* x_2 is MF_{24} *and* x_3 is MF_{35} *and* x_4 is MF_{42} *and* x_5 is MF_{52} *and* x_6 is MF_{61} *and* x_7 is MF_{71} *and* x_8 is MF_{82}, *Then* y_H = (0.6287+ 0.2538x_1 + 0.3483x_2 - 0.1493x_3 + 0.1085x_4 - 0.4197x_5 - 0.4555x_6 - 0.2626x_7 - 0.06333x_8).

Model 3:

If x_1 is MF_{11} *and* x_2 is MF_{23} *and* x_3 is MF_{34} *and* x_4 is MF_{43} *and* x_5 is MF_{54} *and* x_6 is MF_{64} *and* x_7 is MF_{74} *and* x_8 is MF_{84}, *Then* y_H = (0.2227+ 0.009144x_1 - 0.1078x_2 + 0.03565x_3 + 0.1077x_4 + 0.1951x_5 + 0.1998x_6 + 0.08163x_7 + 0.004227x_8).

Model 4:

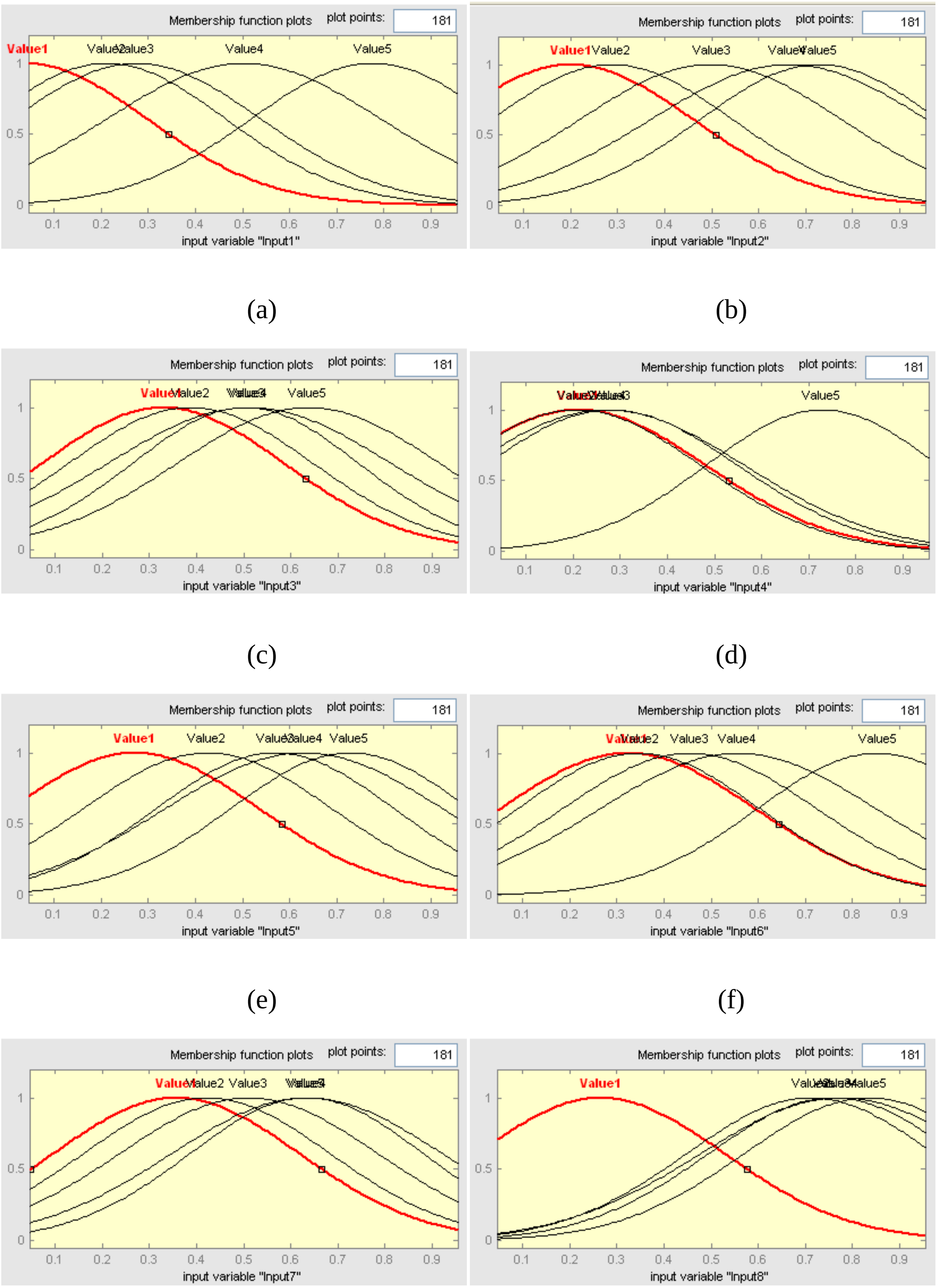
If x_1 is MF_{14} *and* x_2 is MF_{25} *and* x_3 is MF_{32} *and* x_4 is MF_{44} *and* x_5 is MF_{55} *and* x_6 is MF_{62} *and* x_7 is MF_{75} *and* x_8 is MF_{81}, *Then* y_H = (0.2448+ 0.05979x_1 + 0.02159x_2, -0.04047x_3 + 0.2202x_4 + 0.07846x_5 - 0.01265x_6 - 0.01162x_7 + 0.1297x_8).

Model 5:

If x_1 is MF_{13} *and* x_2 is MF_{22} *and* x_3 is MF_{33} *and* x_4 is MF_{45} *and* x_5 is MF_{43} *and* x_6 is MF_{65} *and* x_7 is MF_{73} *and* x_8 is MF_{85}, *Then* y_H = (0.3077- 0.001267x_1 + 0.001715x_2 - 0.291x_3 - 0.1659x_4 - 0.3424x_5 + 0.1052x_6 + 0.496x_7 + 0.2649x_8).

Note: y_H is the predicted value with regard to the rating of handiness of mobile

Figure 5.3 Examples of TSK fuzzy models extracted from the dynamic NF model



(a) (b)

(c) (d)

(e) (f)

(g) (h)

Figure 5.4 MFs of (a) Top Shape, (b) Bottom Shape, (c) Function Button Shape, (d) Layout, (e) Body Length, (f) Body Thickness, and (g) Border Width

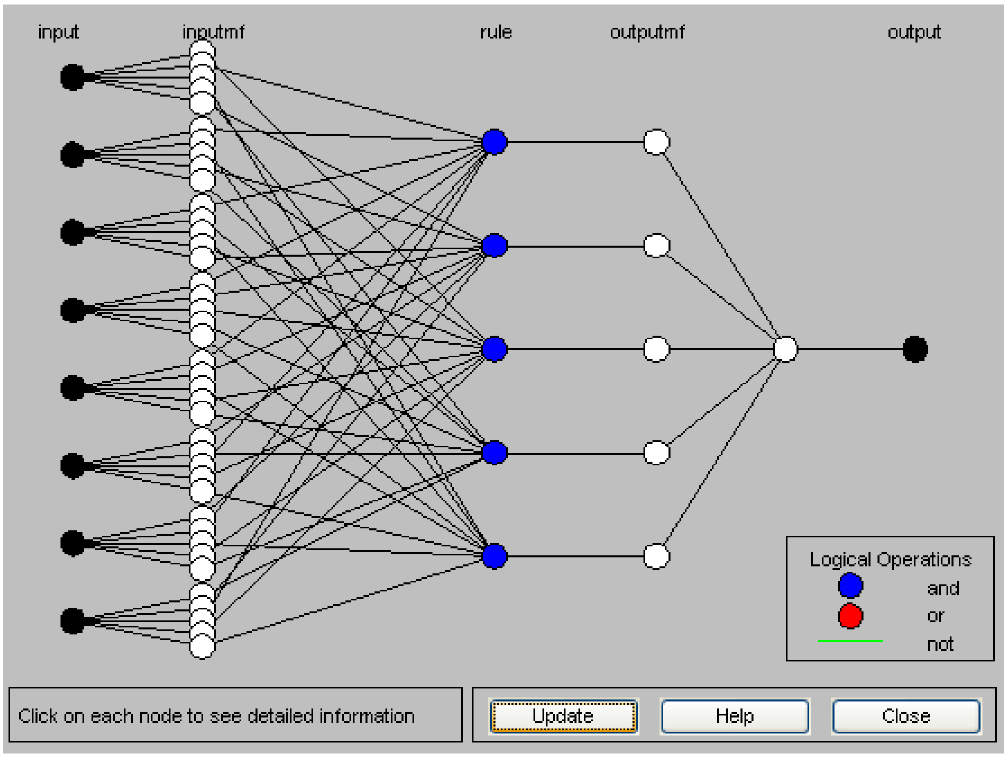


Figure 5.5 Structure of the developed dynamic NF model

5.3.2 Performance of the dynamic neuro-fuzzy model

In this study, a leave-one-out cross-validation was performed to investigate the prediction performance of the proposed dynamic NF model for affective design. Leave-one-out cross-validation was found to have the smallest bias for small data sets (Martens and Dardenne, 1998), and continuous errors (Priddy and Keller, 2005). Since the size of the mobile phone data sets is small and the root mean square error (RMSE), which was employed to evaluate the performance of NF models, is a continuous error, a leave-one-out cross-validation was adopted. The data of 32 mobile phone samples were randomly partitioned into training and test sets. The training set has 31 samples, and the test set has one. The cross-validation test has 32 folds. Each fold of the cross-validation test underwent the replacement of the training and test sets during the training process, such that every sample played the test set role at least once.

Two dynamic NF models, with and without BP training, were tested. Their prediction performance was compared with that of the ANFIS models. First, we attempted to develop an ANFIS model using the MATLAB Fuzzy Logic Toolbox based on the survey data. However, the ANFIS failed to run because the ANFIS structure contained more than 10935 hidden nodes, and it was too complex. As a result, the 'out of memory' error occurred. Two simplified ANFIS, i.e., subtractive clustering (SC)-based and fuzzy *c*-mean clustering (FCM)-based ANFIS models, were employed instead of a fully structured ANFIS (Zadeh and Berkeley, 2001). The hidden nodes were selectively built in the SC-based and FCM-based ANFIS models based on the partitioning results of subtractive clustering and fuzzy *c*-mean clustering, respectively. The SC-based and FCM-based ANFIS models were implemented using the MATLAB Fuzzy Logic Toolbox. The four NF models were trained using the same training data sets. Finally, the trained models were applied to estimate customer affections using the test data sets. The performance of the four models was compared based on the average RMSE and computational time. The average RMSE is defined as follows:

$$Average\ RMSE = \frac{\sum \text{RMSE of test samples}}{\begin{array}{c}\text{Total number of test samples}\\ \text{in the cross-validation test}\end{array}} \tag{32}$$

The results of the cross-validation tests are shown in Tables 5.12 to 5.15. The comparison of the average RMSE of the NF models for various affective data sets are summarised in Figure 5.5. The dynamic NF models and FCM-based ANFIS models perform better than the SC-based ANFIS model in terms of prediction performance on the four product images of 'simplicity', 'uniqueness', 'high tech', and 'handiness'. The test results for ‘simplicity’, ‘uniqueness’, and ‘high tech’ reveal that test errors based on the dynamic NF models without BP training are smaller than those based on the FCM-based models. Moreover, the dynamic NF models with BP training outperform the FCM-based ANFIS models in terms of prediction performance. BP training significantly reduces the errors of the dynamic NF model for ‘high tech’ and ‘handiness’. This finding may be caused by the fact that BP training can fine-tune MFs and improve the prediction accuracy of the local models. The results shown in Tables 5.12 and 5.13 reveal that the errors of the dynamic NF model with BP training are slightly larger than that of the errors of the dynamic NF model without BP training. This finding may be caused by the NF model search with BP training, which can trap a local optimum and induce overfitting. However, dynamic NF models with BP training achieve the best overall prediction performance.

Apart from prediction performance, the test results show that dynamic NF models are more computationally efficient than the other two NF models. The computational time of the dynamic NF models is about 18% to 29% less than that of the two ANFIS models. The computational time of the incremental training for dynamic NF models per update is around 0.018 seconds.

Table 5.12 Test performance of the NF models (simplicity)

Models	**Average RMSE**	**Average Computational Time / second**
SC-based ANFIS	0.2874	0.6921
FCM-based ANFIS	0.166	0.6157
Dynamic NF without BP	0.147	0.4991
Dynamic NF with BP	0.1474	
Average computational time per update of dynamic NF models is 0.01848 seconds.		

Table 5.13 Test performance of the NF models (uniqueness)

Models	**Average RMSE**	**Average Computational Time / second**
SC-based ANFIS	0.2859	0.692
FCM-based ANFIS	0.1086	0.606
Dynamic NF without BP	0.101	0.4876
Dynamic NF with BP	0.1143	
Average computational time per update of dynamic NF models is 0.01806 seconds.		

Table 5.14 Test performance of the NF models (high tech)

Models	**Average RMSE**	**Average Computational Time / second**
SC-based ANFIS	0.464	0.6048
FCM-based ANFIS	0.2941	0.6887
Dynamic NF without BP	0.2927	0.493
Dynamic NF with BP	0.2312	
Average computational time per update of dynamic NF models is 0.01826 seconds.		

Table 5.15 Test performance of the NF models (handiness)

Models	**Average RMSE**	**Average Computational Time / second**
SC-based ANFIS	0.3533	0.6859
FCM-based ANFIS	0.1312	0.6277
Dynamic NF without BP	0.1387	0.5047
Dynamic NF with BP	0.07244	
Average computational time per update of dynamic NF models is 0.01869 seconds.		

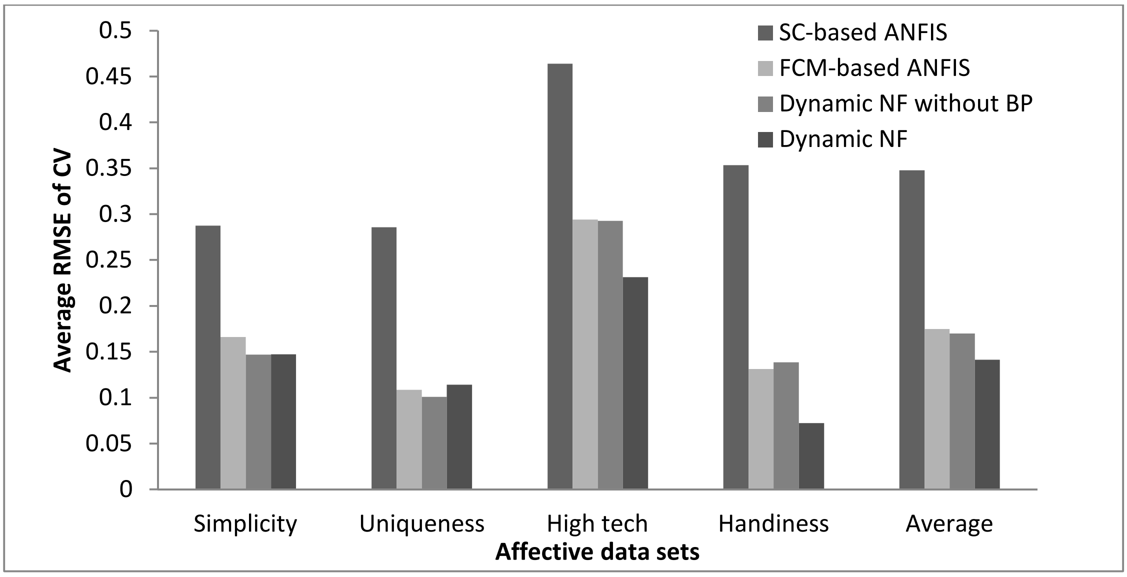


Figure 5.6 Histogram of the average RMSE of the NF models

5.4 Implementation of the design optimisation model

Optimal settings of the design attributes for affective design of mobile phones are determined by developing design optimisation models. In this research, the proposed guided search optimisation approach was implemented to maximise 'handiness' of mobile phone design using the MATLAB software programming language. The GA objective function is to minimise the output of the trained NF model (predicted 'handiness'), which represents 'handiest' in the normalised scale. Hence, the threshold of target value was set to 1×10^{-5} as one of the stopping criteria of the GA optimisation.

Four different GA optimisation strategies were evaluated to investigate the performance of the proposed optimisation approach, including the non-guided search strategy ('No GS'), three guided search strategies using all rules ('GS All R'), only positive rules ('GS +ve R'), and only negative rules ('GS -ve R'). The test on 'No GS' executed the non-constrained GA and no GS operators. In contrast, 'GS All R' applied the constraints and GS operators to thoroughly guide the GA search. 'GS +ve R' adopted only GS operators defined by positive rules, as shown in Table 5.3. 'GS -ve R' performed the constrained GA using the penalty approach, and the constraints were defined based on the negative rules shown in Table 5.3. 'GS +ve R' and 'GS -ve R' were used to investigate the performance of the partially guided search approach when the rule set is incomplete or contains either positive or negative rules only.

Inequity was avoided using the same initial population for the performance test of all four optimisation strategies, instead of the population from random initialisation. This measure ensured that all GA convergences began from the same starting point. For each generation, best fitness value of the population was evaluated with a population size of 50. For the tests of 'No GS' and 'GS -ve R', ρ_c and ρ_m were set to 75% and 25%, respectively. The guided search operators were disabled (ρ_{gs} = 0%). The guided search operators were enabled for 'GS All R' and 'GS +ve R'. ρ_c, ρ_m, and ρ_{gs} were set to 50%, 25%, and 25%, respectively.

5.4.1 Results of design optimisation

The GA convergence results of the four GA optimisation strategies are shown in Figure 5.6. The proposed guided search approaches converged faster than did the non-guided search approaches ('No GS'). All GA models started at the same point, where the best and mean fitness values of the initial population are 0.25 and 0.4, respectively. After 100 generations, the best fitness value gradually decreased from 0.25 to below 0.1 using the 'No GS' approach. In contrast, convergence was dramatically improved by the 'GS All R' approach. Mean fitness value of the population was minimised to nearly zero (smaller than 0.01), and the near-optimal solution was almost found by the

'GS All R' approach after 60 generations. The 'GS +ve R' and 'GS -ve R' approaches also provided notable improvements to GA convergence. However, employing either GS operators or constraints cannot guide the search as effectively as the 'GS All R' search. The 'GS -ve R' approach only slightly impelled the convergence compared with the 'No GS' approach. 'GS +ve R' remarkably accelerated convergence in the first 30 generations. However, convergence became sluggish, and the fitness value was held above 0.5. The 'GS All R' approach yielded the best GA convergence among the four optimisation models.

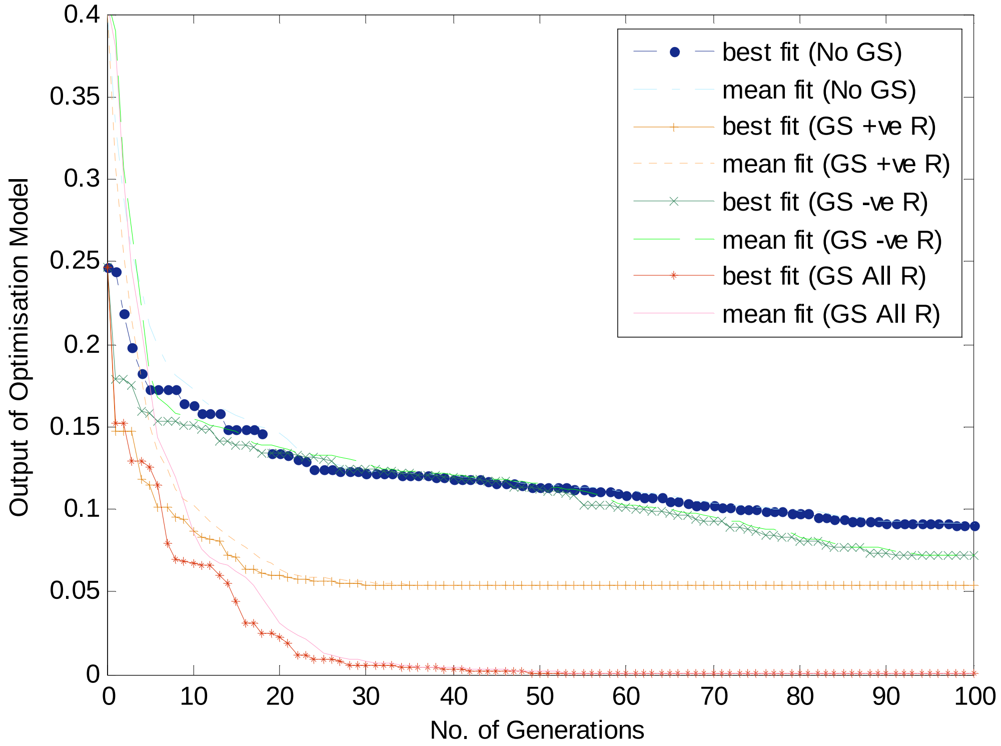


Figure 5.7 Comparison among the convergences of the guided search GAs

The computational times between the guided search and non-guided search approaches were compared. The computational times of the four optimisation strategies are shown in Table 5.16. Six GS operators were defined, and their operating rate ρ_{gs} was set to 25%. Three constraints were set as shown in Table 5.3. The computational time of the 'GS -ve R' model only required 0.4% more than that of the 'No GS' model in terms of average computational time per generations. The 'GS All R' and 'GS +ve R' models required about 40% more computational time per generations than the 'No GS' model. More computational time was required for the objective function evaluation and selection of temporary solutions produced by GS operators. However, the superior searching ability of the 'GS All R' model overcame this problem. The 'GS All R' model reached the target fitness with the minimum number of generations and with the shortest total computational time.

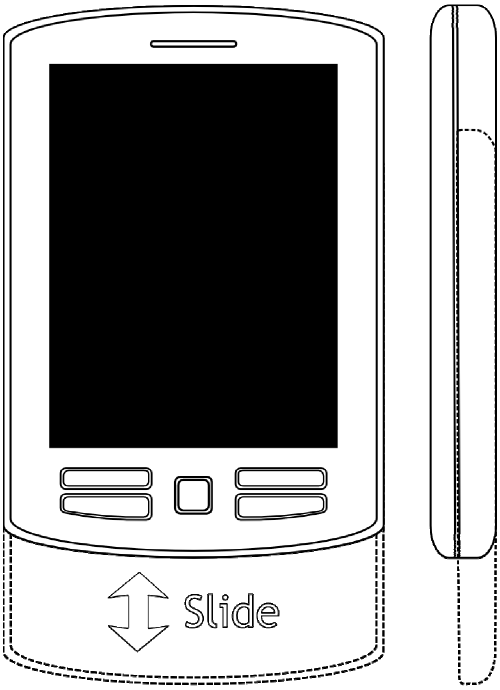
Table 5.16 Comparison of the computational time of the guided search genetic algorithms

GA Optimisation Strategy	No. of Generations Elapsed	Total Computational Time Used / second	Average Time per Generations / second	Best Fitness (Minimising)
'No GS'	301	20.02	0.0665	0.1844
'GS +ve R'	213	20.05	0.0941	0.0540
'GS -ve R'	300	20.03	0.0668	0.0779
'GS All R'	130	12.20	0.0938	0.0000

The optimal attribute settings of mobile phone design obtained by the four search strategies are shown in Table 5.17. Among the four optimisation models, the 'GS All R' model yields the best solution of a handy mobile design design, which has the smallest fitness value. Based on the recommended attribute setting, the affective design of a new mobile phone was generated and is shown in Figure 5.8. It is a small slide-type mobile phone, whose length and thickness are 25% and 41% smaller than the average length and the thickness of the 32 mobile phone samples, respectively. The recommended design adopts a small function button and a slide layout that uses a minimal space to maximise the manipulability of mobile design.

Table 5.17 Attribute settings of mobile phone design obtained by the guided search genetic algorithms

GA Optimisation Strategy	**'No GS'**	**'GS +ve R'**	**'GS -ve R'**	**'GS All R'**
Best Fitness (Minimising)	0.1844	0.0540	0.0779	0.0000
Top shape (A_1)	Line ($x_{1,1}$)	Curve ($x_{1,3}$)	Curve ($x_{1,3}$)	Arc ($x_{1,2}$)
Bottom shape (A_2)	Line ($x_{2,1}$)	Arc ($x_{2,2}$)	Line ($x_{2,1}$)	Arc ($x_{2,2}$)
Function button shape (A_3)	Large square ($x_{3,4}$)	Small square ($x_{3,3}$)	Large round ($x_{3,1}$)	Small square ($x_{3,3}$)
Layout (A_4)	Bar ($x_{4,1}$)	Large screen ($x_{4,3}$)	Large screen ($x_{4,3}$)	Slide ($x_{4,2}$)
Body length, mm (A_5)	77.8	71.7	107.6	73.3
Body width, mm (A_6)	54.0	51.3	50.8	50.6
Body thickness, mm (A_7)	8.9	8.9	8.9	8.9
Border width, mm (A_8)	0.94	0.94	0.94	0.94



settings
one design

Arc (x_{12})

2): Arc (x_{22})

n shape (A_3):
3)

le (x_{42})

: 73.3 mm

50.5 mm

A_7): 8.9 mm

): 0.94 mm

Figure 5.8 Affective design of a new mobile phone generated by ‘GS All R’ model

Chapter 6 Discussion

Some limitations of the proposed methodology and the development of the proposed intelligent system are discussed in this chapter.

6.1 Discussion on the proposed methodology

In affective design, customer surveys are commonly used to acquire customer affections towards products. Quality of surveys is important for acquiring good survey data for analysis, affecting the consistency of survey data and correlation validity for data analysis (Krosnick, 1997). In the present study, the SD method was adopted for collecting customer affections through questionnaires (Chapter 3). The number of options in the rating scale should be appropriate for respondents to indicate their preferences. Otherwise, respondents may be forced to give ratings that do not entirely represent their preferences. The inappropriate ratings can increase inconsistency of survey data and errors in the data analysis (Tarantino, 2008). In addition, inconsistency of survey data can be produced because of the use of inappropriate wordings in questions, especially affective words describing the SD scale. If ambiguous words are used in the questions, the discrepancy in understanding among respondents and the possibility of deviating from the target meaning of the questions are greater. The optimal affective words for describing the SD scale can be investigated by multivariate statistical analyses, such as factor analysis, principal component analysis, and multidimensional scaling (Barone *et al.*, 2009; Nagamachi *et al.*, 2008). The measurement of the ambiguity in the survey data has been discussed by Lai *et al.* (2005a).

In the present study, the inconsistency of survey data may exist and affect the results of the MOGA-based rule-mining model and dynamic NF model. In the MOGA-based rule-mining model, approximate rules are mined from raw survey data, and the extent of their approximation can reflect the inconsistency of survey data. When survey data are highly inconsistent, the extent of approximation of generated rules tends to be greater. Hence, the definability of approximate rules is low and less interesting and useful for users. For the dynamic NF model, accuracy of developed models can be affected by the inconsistency of training data. Highly inconsistent data lead to large errors of correlation and regression coefficients in a regression analysis (Tarantino, 2008). As RLS was adopted as the regression method in the dynamic NF model, these errors form part of the total error. Moreover, there are other sources of errors, such as outliers and overfitting of the model training.

Sampling errors may occur in design of experiments. Conducting a survey that involves an entire sample set (i.e., all possible combinations of design attribute settings) is difficult. Typically, survey samples are chosen through a random sampling method or an orthogonal array method. An uneven sampling may result in some areas of the design space that may be sampled less or not at all. Referring to the NF model, the result with a higher error may be caused by a sampling issue.

Measurement errors may arise during the measurement and classification of design attributes from real product samples used in a survey. The values of quantitative design attributes (e.g., dimensions of features) are measured using measurement tools, such as meters and gauges. However, defining and classifying categorical design attributes and their categorical options typically require expert knowledge. Completely eliminating human subjective judgment is not easy when classifying categorical design attributes. The definition of categorical design attributes can be ambiguous. For example, a slightly tapered quadrilateral can be recognised as a rectangular shape because of individual variations in visual judgment.

The number of design attributes can affect the performance of the intelligent system. Although more design attributes to be considered would lead to more detailed study of a product design and enrich the information for machine learning, increase in the number of design attributes would adversely affect the performance of the intelligent system because the model becomes more complicated. Generally, if more attributes are involved, a larger number of samples for training the models is required. Alternatively, we can introduce some techniques to the screen out nonsignificant attributes . In the proposed intelligent system, the rule mining model generates rules with minimising the rule complexity and could play a role of attribute selection. However, a comprehensive model is required to act as the design optimisation model for generating an entire design. The dynamic NF model is therefore built with all design attributes in this study. Excessive attributes can easily generate noise data if the number of design attributes increases. The noise would affect the clustering results of data in the attribute space, parameter settings of fuzzy membership functions and formulation of local fuzzy models during the training of the dynamic NF model.

The proposed methodology can be applied to support affective design of various products, besides mobile phone design used for the case study such as automobiles, furniture, cosmetic containers, and many products used in daily life, as mentioned in previous studies (Catalano, 2002; Nagamachi, 2002). The methodology is quantitative to analyse customer affections towards products based on data, and flexible to deal with different design attributes regardless of the configuration of design attributes based on combinatorial design, parametric design, or hybrid approach.

In the previous studies of design for product functionality and defining product specifications, elicitation of correct data from customers in the early stage of new product design is challenging. If the product idea is new to customers, they may not be able to state their needs of product functionality clearly. Affective design is to study the emotional aspect of products, and is quite different from design for product functionality. Customer affection is close to intuition and sensation which is an instinct response. Comparing with the elicitation of customer needs of functionality, it is less difficult to elicit customer affection in the early stage of new product design. Customers usually can express their affective feelings on products by browsing through sketches, drawings, images and/or prototypes of them.

With the affective data sets obtained from the survey and the design data sets compiled by designers, the proposed intelligent system can be applied to perform the knowledge discovery and optimisation of affective design of products. The short computational times of the dynamic NF model and guided search design optimisation model make the proposed intelligent system suitable as a kernel of an interactive design system (Jiao *et al.*, 2008; Kim and Cho, 2000; Yanagisawa and Fukuda, 2005) or a decision support system for customized products. Suppose a customer inputs his/her desired affection on a product into the decision support system through a short questionnaire. An optimal affective design solution is then generated to satisfy customer affection in a minute. However, the design features are pre-defined, and new design features cannot be generated in the proposed methodology. It limits design generation by combining the pre-defined options of the design attributes.

The proposed intelligent system was developed with consideration of data ambiguity and inconsistency, which is a fundamental issue of affective design. A small sample size, which may be due to the shortage of product information obtained in early design stage, and cost and time-saving in marketing surveys, is another challenge of affective design studies. The case study of mobile phone design demonstrated how the proposed methodology deals with the challenges. Based on the implementation results of the case study, the proposed rule-mining and dynamic NF-based modelling approaches yield high and stable performance for various data sets of mobile phone design. The proposed approaches are able to improve the quality of rules and models for reasoning affective design. Although the robustness of the proposed system was not investigated in details due to the limited time of the research study, the implemented results show that the robustness of the proposed system is quite satisfactory.

6.2 Discussion on the MOGA-based rule-mining model

Approximate rules are more suitable than crisp rules when ambiguity and fuzziness exist in survey data. They can capture the vague regions of customer affection. However, approximate rules are inadequate for the distribution of affective data. As a result, the distribution and central tendency of affective data cannot be considered in the approximate rules.

The maximum number of rules in a rule set is the number of rules generated at the first stage of rule mining. At the first stage of rule mining, the GA population size must not be too small, otherwise the number of rules generated is restricted at this stage. At the second stage, the rule can be refined or purged, but extra rules cannot be added because of the adopted fixed-length chromosome structure. Given that the MOGA may over-converge at the first stage of rule mining, a limited number of rules may be generated. Supplementary rules may be required to refine the rule set. Spare genes can be added to the chromosome of the second stage of rule mining to increase the capacity of the rule sets.

The activation threshold τ is another factor that can affect the number of rules in a rule set at the second stage of rule mining. Less important rules are excluded from the rule set if their weights are smaller than τ. A high activation threshold value is preferred, and the value of τ is assumed 0.8 for selecting the significant rules for the rule set. However, an increase in the value of τ reduces the number of rules selected for the rule set and vice versa.

NSGA-II was employed to solve the multi-objective rule-mining problem. The crowding mechanism of NSGA-II was applied to preserve population diversity. The population is ranked according to the objective function values and crowding distance. Two possible issues on diversity of rules are raised by the crowding mechanism of NSGA-II. First, NSGA-II returns the best N_{pop} solutions in the Pareto set but not the entire Pareto solution set. NSGA-II does not contain external memory for storing non-dominated sets (Coello Coello, 2006). It can only return solutions that survive in the population. Second, NSGA-II does not examine the similarity of each gene. There can be a lack of consideration for diversity in the rule condition values. Crowding distance is calculated from the difference in the objective function values from two adjacent solutions in the population (Deb *et al*., 2002). Supposing that the rules obtained from two adjacent solutions have notable differences in the objective function values (the criteria of rule mining), then there may only be slight deviations between their rule condition values. This problem may result in similar rules obtained from the first stage of rule mining. However, rules can be refined considering the rule interaction, and the diversity of rules can be restored through mutation at the second stage of rule mining. Moreover, a rule set containing similar rules has high complexity. It has a low survival rate because one of the objective functions is to minimise the complexity of the rule set.

The maximum number of generations was adopted as a stopping criterion of MOGA. Single-objective GA can be terminated normally when its convergence remains still over several generations and reaches a satisfied fitness value. However, determining the satisfied trade-off among multi-objective functions of MOGA is difficult. A higher maximum number of generations can be adopted to ensure the convergence of MOGA, but it requires a long computational time.

6.3 Discussion on the dynamic NF model

The dynamic NF model is better than the ANFIS model in handling high-dimensional problems because it can generate local models on demand. The structure of an ANFIS becomes very complex if the number of inputs or MFs is large. Nevertheless, the dynamic NF model has its shortcomings. In the training process of the dynamic NF model, partitioned regions are formed using a clustering method for training local models. The entire input space may not be covered by the partitioned regions of the clusters. The dynamic NF model can produce accurate predictions if the inputs of a data instance (i.e., attribute settings of a product sample) are inside the regions. Its predictions are less accurate if data inputs are outside the regions.

Every update of the ECM produces a constant clustering result of the design space (input variables). The clustering analysis of the design space is only required once. In such partial dynamic cases, fuzzy c-mean clustering method (FCM) can be employed instead of online ECM. ECM is ideal for fast online clustering, which does not have any optimisation algorithm for tuning the centre and radius of each cluster (Kasabov, 2007b). In contrast, FCM partitions data points based on the minimisation of distances between points and cluster centres. In general, FCM is more robust than ECM. RLS is then used to find local models from each cluster for the incremental training of dynamic affective data.

Nevertheless, ECM is more effective than FCM if new product samples are added to the study. ECM can adopt new design patterns to create a new cluster or update the existing clusters efficiently. The errors of clustering based on ECM are minimised by performing a post-optimisation process to fine-tune the cluster centres and radii, which are obtained based on ECM (Kasabov and Qun Song, 2002; Kasabov, 2007b).

Forgetting factor was introduced to handle time-varying consumer affections in the dynamic NF model. Previous studies of affective design developed affective relationship models based on a time-independent (static) scenario. In real life, customer affection towards a product is changing over the time in a fast-changing market. There is a need of studying the latest design trend (Hsu *et al.*, 2000). For example, an impact on the customer affection towards a product occurs when a new competitive product launches. The time-varying customer affections would cause inconsistency of the affective data gathered from the beginning to the end of the survey period. The proposed dynamic NF model employs a forgetting factor, which acts as a weight on the data instances, to compensate the time-varying effect. Higher weights are exerted to the recent data while lower weights are applied to the past data. In the other words, the latest data set is assumed the most important, and past data sets become less significant for model training. The value of the forgetting factor is important for controlling the fading rate. Kasabov (2002) suggests that the typical range of the forgetting factor is between 0.8 and 1 for DENFIS. For a stable market, the change of customer affection towards a product is small. The value of forgetting factor can be set equal to one, and all data have the same weight that nothing is forgotten. For a dynamic market, the value of forgetting factor is set smaller than one to deal with time-varying effect. Its value may be determined according to the time interval between two sequential records. When the time interval is short, the value of forgetting factor ought to be higher and close to one. The past data have a higher referential value for the estimation of the recent customer affection, and more previous data are used for model training. On the contrary, the referential value of the past data decreases with time, when the duration of a survey period is long and the market is known as fast-changing. A smaller value of forgetting factor should be chosen, so that historical data that are collected before a certain time period are neglected in the model training. The dynamic NF model is trained to memorise the recent data rather than the past data, thereby better estimating the recent customer affection.

In the present study, a constant forgetting factor value of 0.95 was used in batch incremental learning because the survey was conducted in one week. The time effect on customer affections between any two successive respondents is insignificant. Considering the cases of inconsistent time interval, the variable forgetting factor can be used to adjust influence (Zhuang, 1998).

6.4 Discussion on the design optimisation model

A major advantage of the GA is its effectiveness and reliability in searching for a global optimum. In the current case study, the results show that the proposed guided search GA performs better than the non-guided search GA in reaching for global optimal solutions. However, the rule guides need to be in accordance with the NF model prediction. Otherwise, a global optimal solution may not be found by the guided search GA approach because of two reasons. First, the search space is smaller, as the constraints introduced are improperly defined by the negative rules. Thus, the generated solution may be a local optimum instead of a global optimum. Second, the GS operators may adversely affect the convergence of GA convergence. In Figure 5.6, the results of ‘GS +ve R’ show that the GA search converges quickly at the beginning but comes to a standstill before reaching the target fitness. Population diversity is probably reduced by the GS operators because there is a higher survival rate for candidate solutions that contain the GS data structure. If the mutation rate setting is too low, the population diversity may not be restored.

The prediction accuracy for the NF model and the rules are important for finding a global optimum. Users can access rule quality and select rules based on their expert knowledge. The chance of the global optimum existing within the constrained regions is higher if the regions are defined by less number of confident rules. Population diversity is also important for global search. Diversity can be maintained better by increasing the mutation rate and decreasing the rate of applying the GS operators. If the target fitness cannot be reached by the GS approach, studying whether the NF model has been properly trained becomes necessary.

Besides the validation of the rules and the prediction model, the validation of the recommended attribute settings, which are generated by the design optimisation model, is also important. The validation of the recommended attribute settings has two possible cases. If the database contains similar design samples whose attribute settings are the same as the recommended attribute settings, the customer affection of the recommended attribute settings can be validated by simply comparing with the existing data. When similar design samples cannot be found in the existing data set, a new survey is needed to study whether the design based on the recommended attribute settings correctly matches to the desired customer affections or not. Designers who follow the proposed methodology have to prepare an industrial design of the product which is based on the recommended attribute setting. Then, an SD survey is conducted to acquire the customer affection of the new design.

In the current case study, the guided search GA approach can find an optimal solution with less number of generations and less computational time compared with the GA approach without a guided search. However, models applying the GS operators (‘GS All R’ and ‘GS +ve R’) have a longer computational time per generation, as shown in Table 5.16. The computation time of the guided search increases as the number of positive rules used to set the GS operators increase. An additional evaluation of the objective function is performed to obtain the fitness value of the temporary solution for each application of a GS operator. If too many rules are set as GS operators, the computational efficiency of the GS strategy can be largely affected.

A typical limitation of applying GAs for solving optimisation problems is that only near-optimal solutions can be generated. Further studies are required to find a better optimal solution using non-heuristic search algorithms.

Chapter 7 Conclusions and Future Work

This chapter summarises the main idea of the research, and its results and contributions are highlighted. Suggestions for future work are also presented.

7.1 Conclusions

At present, customers consider the tangible and emotional aspects of products. Products with good affective design can attract customers and influence their choices. Affective design of products is to develop a product that satisfies the affective needs of customers. It involves a mapping process from the affective needs in the customer domain to the design attributes in the product domain.

Creating a model based on relationships between customer affections and design attributes of products is challenging because of the fuzzy and non-linear characteristics of these relationships. In recent years, some computational intelligence techniques have been attempted in the research on affective design. The research approaches are mainly divided into two types, namely, the model-based and rule-based approaches. In the current research, a methodology and an intelligent system are proposed for supporting affective design. The system was developed based on the rule-based and model-based approaches. It contains three models: a MOGA-based-rule-mining model, a dynamic NF model, and a design optimisation model.

In the case study of affective design for mobile phones, a MOGA-based rule-mining model was developed to mine rule sets. Eight-fold cross-validation tests were conducted. The test results indicate that the overall support rate of the mined rule sets is 93.75%. The results are better than those based on the DRS-based rule-mining approach. The dynamic NF model displays better prediction performance and shorter processing time compared with the SC-based and FCM-based ANFIS models. The performance of the dynamic NF models with BP training is the best among the NF models in the cross-validation tests. In addition, the dynamic NF models reduce the computational time by 18% to 29% compared with the other two models. The fast incremental training process of the dynamic NF models enables an effective model update and maintenance in the long term. Based on the developed rule sets and dynamic NF model, the relationships between customer affections and design attributes of mobile phones can be modelled. Finally, a design optimisation model was developed to generate the optimal design attribute settings of a new mobile phone. The rules generated serve as constraints when searching for optimal settings. The design rationale of each recommended solution can be recognised from the corresponding rules. The recommended solutions and their design rationales are useful for supporting affective design of products.

The major contributions of the research are summarised as follows:

1. A new methodology for supporting affective design was proposed, by which optimal design attribute settings of affective design of products can be determined.

2. A novel two-stage MOGA-based rule-mining approach was proposed to generate approximate rules for studying affective design. A robust MOGA-based rule-mining approach was adopted and approximate rules were introduced into the MOGA-based rule-mining model. Comparing with the DRS-based approach, the proposed rule-mining approach is more robust to extract rules which can estimate the lower and upper limits of the customer affection induced by design patterns.

Thus, the proposed approach can be used to deal with ambiguity and preference order in survey data.

3. A new dynamic NF-based modelling approach to modelling the relationships between customer affections and design attributes for affective design was proposed. The dynamic NF model enhances the effectiveness of training and updating the NF-based prediction models for affective design. Prediction performance and computational time of the proposed approach were found better than those of the SC-based and FCM-based ANFIS in the validation tests. In addition, the proposed approach can deal with a larger number of inputs. The conventional ANFIS results in long computational time or 'run out of memory' errors when there are too many inputs.
4. A novel guided search GA approach was proposed to generate optimal design attribute settings for affective design. Constraint handling and guided search operation, reasoning based on mined approximate rules, were introduced into the optimisation model to guide the GA search and lead to desirable solutions. The guided search GA approach outperforms the GA approach without the guided search strategy in terms of better GA convergence and shorter total computational time.
5. A novel intelligent system for supporting affective design was developed based on rule-based and model-based approaches. The mined rules not only can provide rule-based knowledge of affective design for users but also serve as guides to the design optimisation process of the system.

7.2 Future work

Some future works related to this study are suggested as follows.

The generated approximate rules are inadequate to consider the distribution of survey data, as mentioned in Section 6.2. Future work may involve the concept of fuzzy MFs to consider the data distribution better. The values of approximate rules can be justified by comparing them with fuzzy membership models. The development of an effective stopping criterion for MOGA rule-mining can be studied in future research. Goel *et al.* (2010) discussed more effective termination strategies and stopping criteria for MOGA, such as consolidation ratio and improvement ratio of non-dominance-based convergence. Their adoption may eliminate excessive generations and solve the optimisation problem more efficiently.

As mentioned in Section 6.3, the performance of the dynamic NF model can be affected by the forgetting factor value. The optimal value of forgetting factor is currently found with a sensitivity test. However, the process is time consuming. The dynamic NF model involves BP training to adjust its fuzzy MF. The forgetting factor value can be adjusted using the BP training algorithm. The methods of optimising the forgetting factor can be explored in future research.

Another future work is related to the application of the dynamic NF modelling. Some major advantages of the dynamic NF model are its computational efficiency and ability to update a developed model through incremental learning, instead of retraining the entire model. Virtual KE (VKE) (Nagamachi, 2002, 2006) and interactive evolutionary design systems (IEDS) (Kim and Cho, 2000; Yanagisawa and Fukuda, 2005) are technologies for designers to create their designs using virtual reality and evolutionary algorithms such as GA. Users have to evaluate numerous design candidates on the screens until the convergence of the most preferred design is obtained by GA. During the evaluation process, the dynamic NF model can learn about affective relationships from records through incremental training. Moreover, the dynamic NF model can be used to predict user preferences, and guide crossover and mutation operations to improve GA convergence. GAs can be costly, but dynamic NF model is a fast online model. By integrating dynamic NF model with IEDS, the computational efficiency can be improved, and the instant feedback of interactive design systems can be supported.

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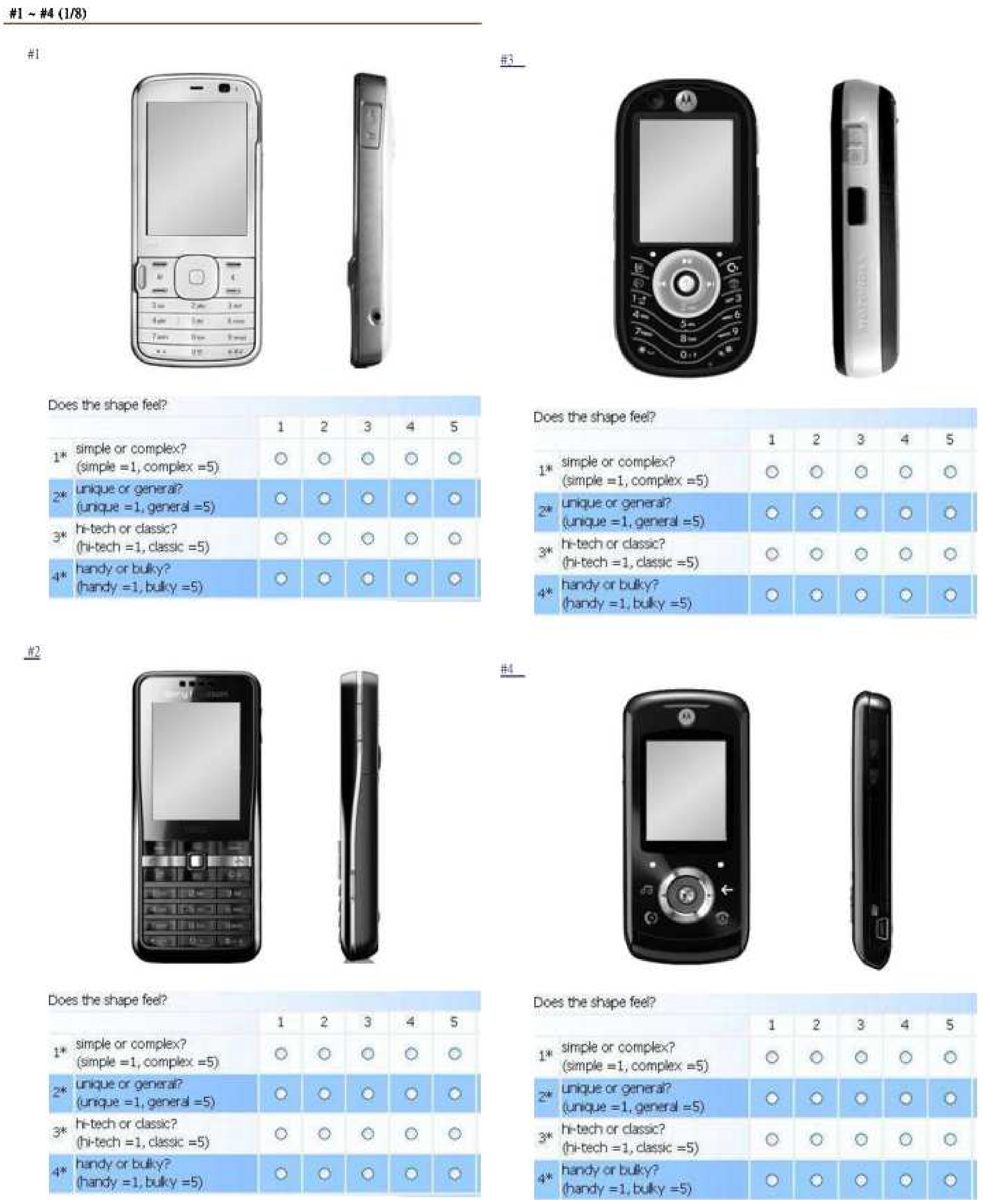
Appendix Questionnaires of affective survey on mobile phone design



#1 ~ #4 (1/8)

#1

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#2

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#3

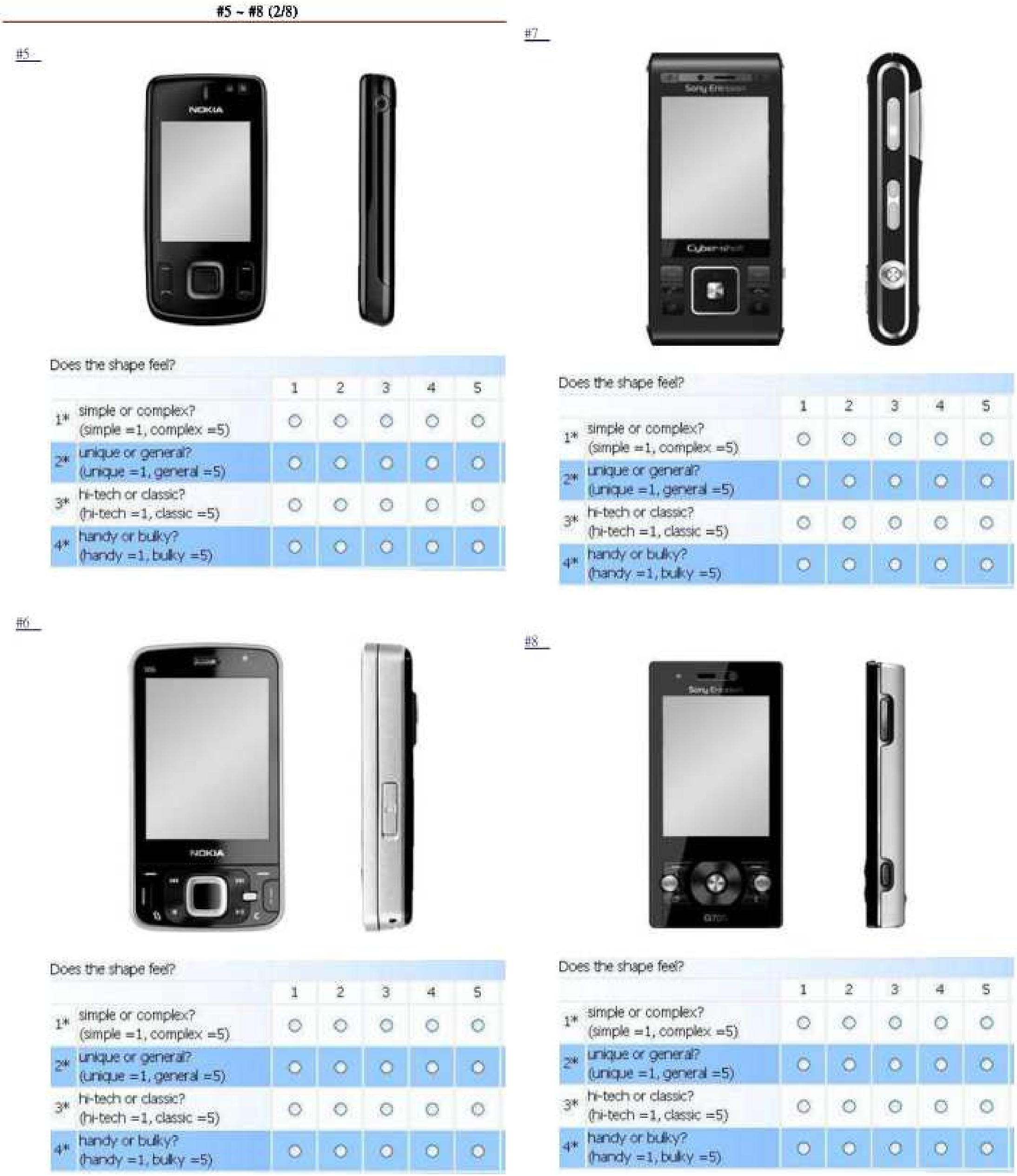
Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#4

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○



#5 ~ #8 (2/8)

#5

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#6

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#7

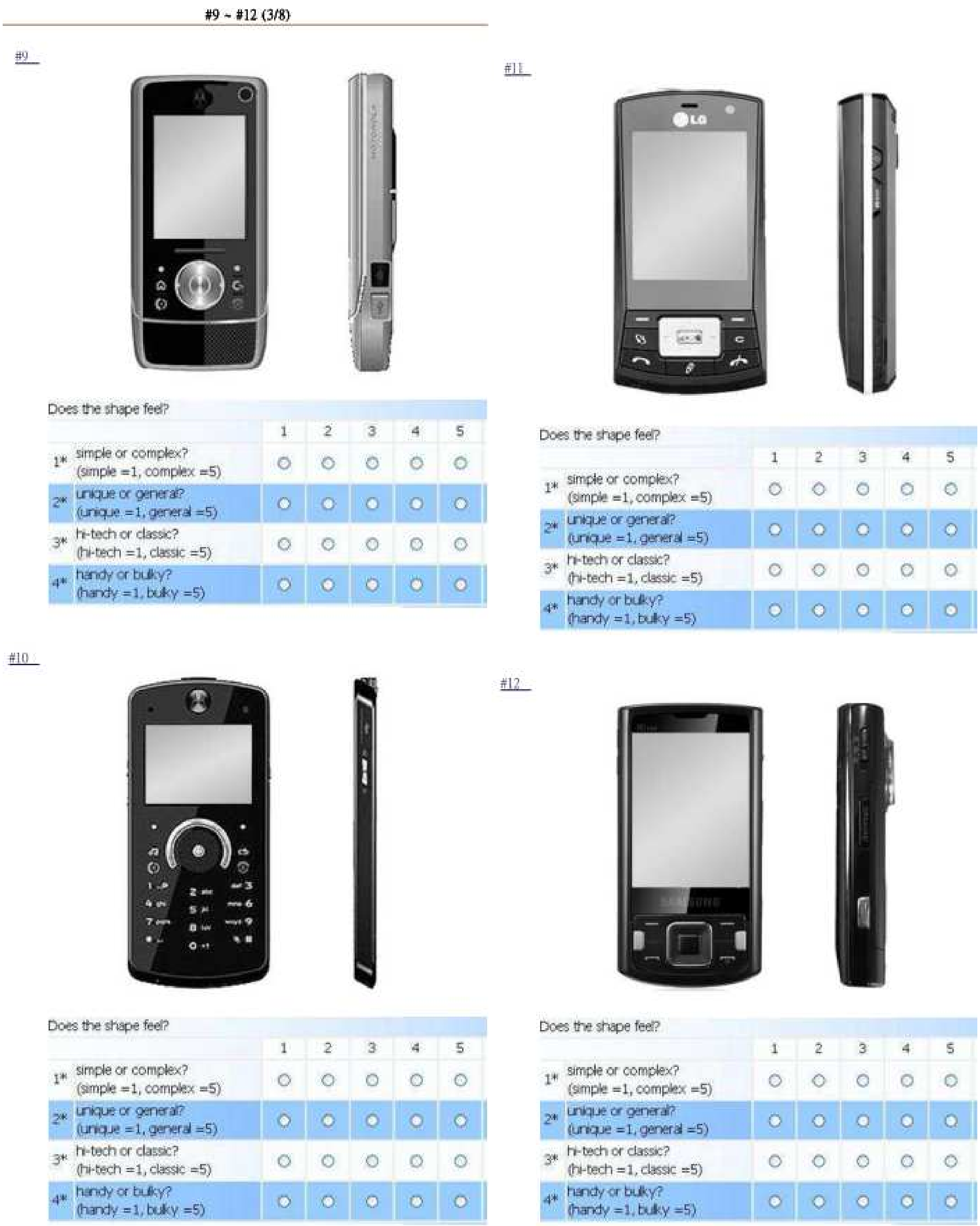
Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#8

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○



#9 ~ #12 (3/8)

#9

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#10

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#11

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

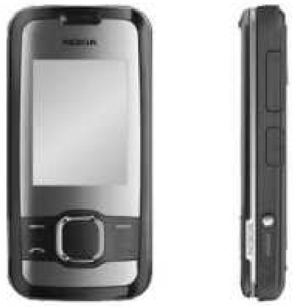
#12

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#13 ~ #16 (4/8)

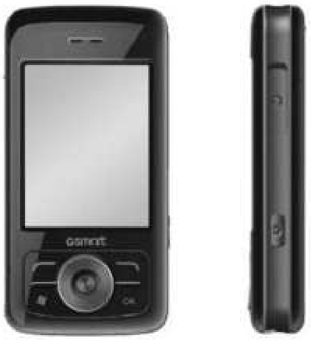
#13



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

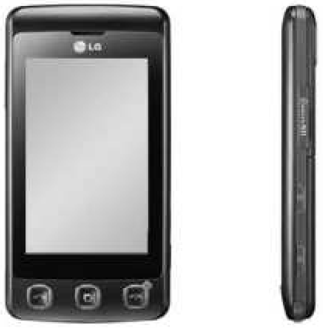
#15



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

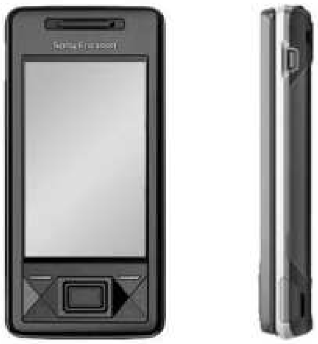
#14



Does the shape feel?

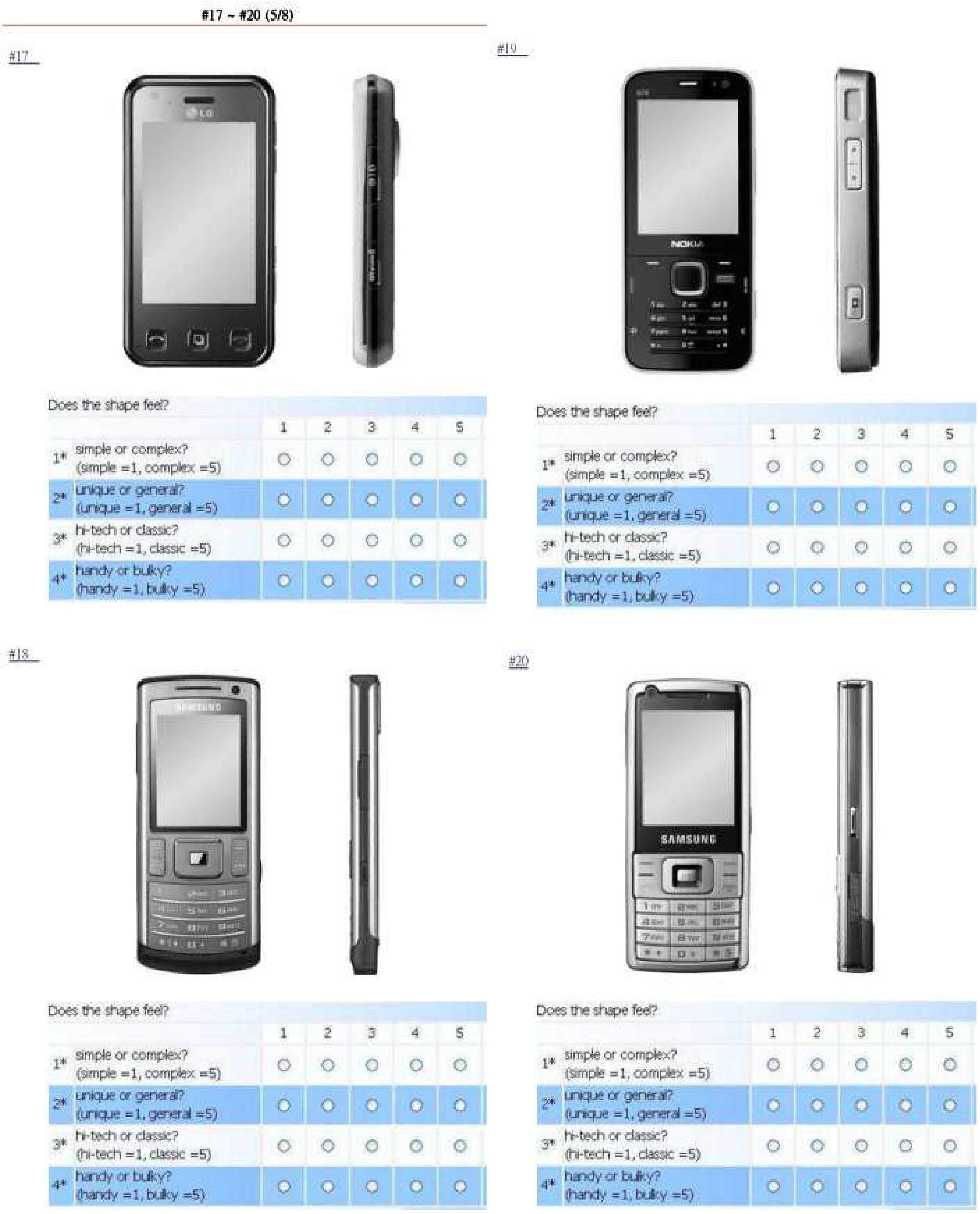
		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#16



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○



#17 ~ #20 (5/8)

#17

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#18

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#19

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

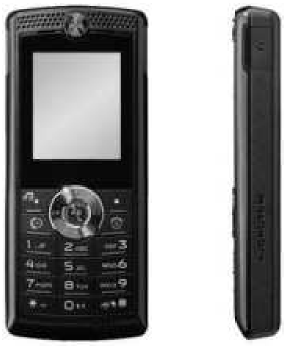
#20

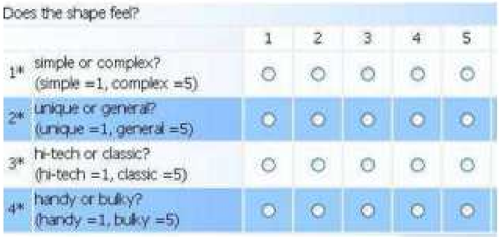
Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#21 ~ #24 (6/8)

#21

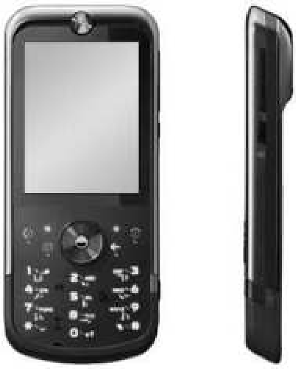


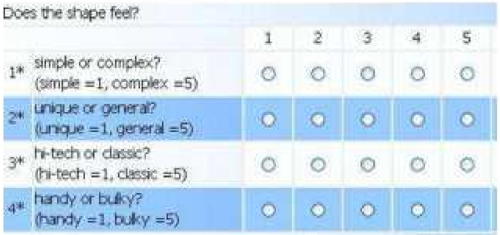


Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#22

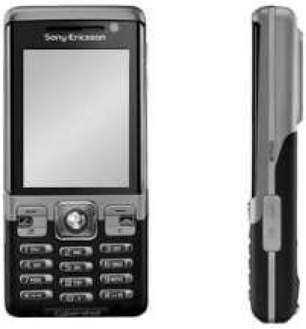


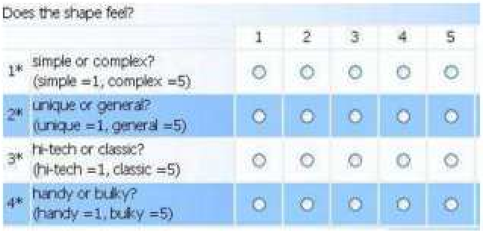


Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#23

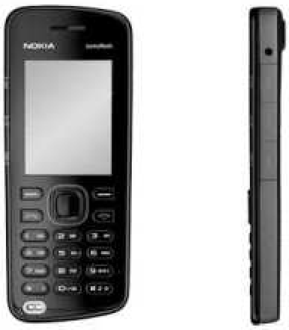


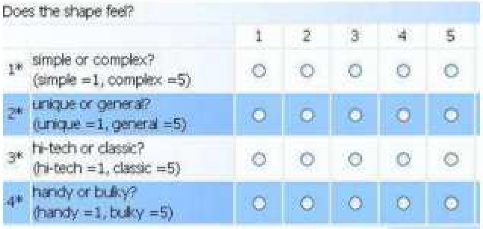


Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#24



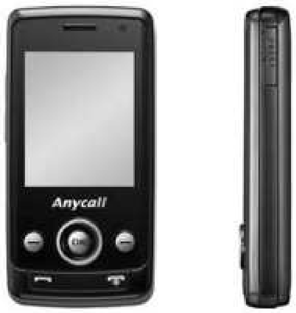


Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#25 ~ #28 (7/8)

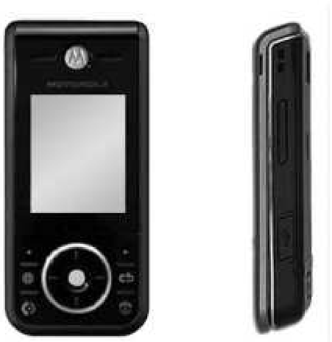
#25



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

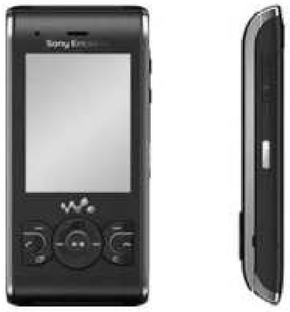
#26



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

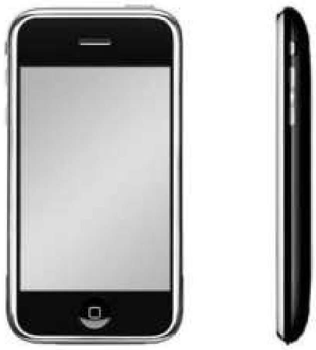
#27



Does the shape feel?

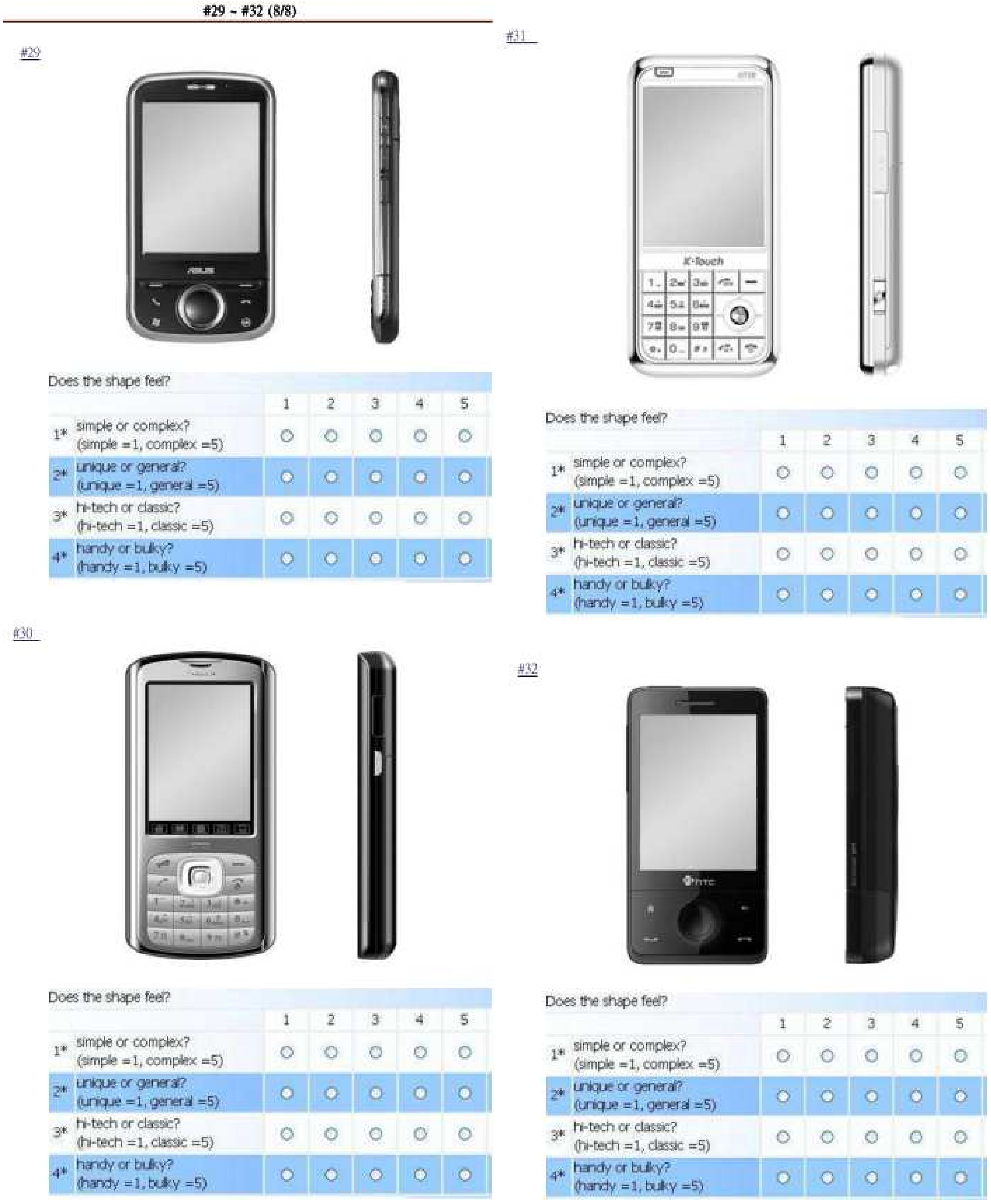
		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#28



Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○



#29 ~ #32 (8/8)

#29

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#30

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#31

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

#32

Does the shape feel?

		1	2	3	4	5
1*	simple or complex? (simple =1, complex =5)	○	○	○	○	○
2*	unique or general? (unique =1, general =5)	○	○	○	○	○
3*	hi-tech or classic? (hi-tech =1, classic =5)	○	○	○	○	○
4*	handy or bulky? (handy =1, bulky =5)	○	○	○	○	○

- END -