Abstract
Industrial product form design has become consumer-centred. Affective responses related to consumers’ affective needs are considered invaluable for product form design and have attracted increasing attention. When designing product forms, designers should thoroughly understand the design knowledge concerning multiple affective responses and design variables. This paper proposes a systematic approach to extraction of design knowledge by using multiobjective optimisation and rough sets. Design analysis is first employed to determine design variables and multiple affective responses. As per the results, a multiobjective optimisation model is constructed that involves optimising the multiple affective responses. An improved version of the strength Pareto evolutionary algorithm (SPEA2) is adopted to solve the multiobjective optimisation model and generate the Pareto optimal solutions. Based on these Pareto optimal solutions, rough sets are employed to extract design knowledge that is common to these Pareto optimal solutions. A car profile design was employed as a case study to illustrate the proposed approach. The results suggest that the proposed approach is time- and cost-efficient and can effectively extract design knowledge that provides suitable insight into product form design.

Keywords: Kansei engineering, Affective responses, Product form design, Multiobjective optimization, Rough sets

1. Introduction
With increasing competition in contemporary markets, companies must design products which can meet the needs of consumers. Affective responses, which reflect consumers’ affective needs on product form, have gained particular attention in industrial design field (Dahlgaard and Nagamachi, 2008). Affective engineering, also known as Kansei engineering, concentrates on translating the affective responses of consumers into design variables (Nagamachi, 2002). The use of affective engineering has been considerably successful for product form design (Kittidecha and Marasinghe, 2015).

When performing product form design, designers should thoroughly understand the design knowledge related to affective responses and design variables. A number of studies have been carried out on the discovery and acquisition of design knowledge (Chien et al., 2014; Shieh et al., 2016; Zhai et al., 2009a). However, in these studies, numerous design samples were required, which increased the cost of and time required for the design procedure. Moreover, few mechanisms exist for confirming whether the design samples used for extracting design knowledge are optimal. Thus, the extracted knowledge cannot provide deep insight into product form design. Analysing a set of optimal solutions that specify certain design variables and their affective responses enables researchers to determine whether any common knowledge exists between all or any of these optimal solutions. Such knowledge is of considerable importance for designers. Therefore, obtaining optimal design solutions is essential to effectively extracting design knowledge.

The affective responses of human towards products comprise multiple facets. Therefore, the problem of deriving optimal solutions that satisfy multiple affective responses can be viewed as a multiobjective optimisation problem (MOP), which is a critical type of problem in affective engineering (Jiang et al., 2015; Shieh et al., 2018). The
traditional approach for solving an MOP involves integrating multiple objectives into a single-objective and then using the optimisation algorithm to derive a single optimal solution (Guo et al., 2014; Hsiao et al., 2010); that is, the MOP is converted into a single-objective optimisation problem. This approach is simple and efficient; however, its limitations prevent consideration of all possible solutions, and it cannot provide sufficient knowledge regarding design variables and affective responses. Thus, the traditional optimisation approach constrains their usefulness to designers (Shieh et al., 2017). By contrast, a multiobjective optimisation approach does not require the integration of multiple objectives and can provide numerous Pareto optimal solutions. Based on these Pareto optimal solutions, designers can extract knowledge for product form design (Deb and Srinivasan, 2006).

Rough sets are an effective and systematic method for knowledge discovery. They can be used to analyse all types of data, including linear and nonlinear data (Nagamachi et al., 2006). The main difference between rough sets and other approaches coping with uncertain problems is that rough sets do not require any prior information beyond the problem itself (Li et al., 2017). Because of these advantages, rough sets have been used in many studies for extracting design knowledge (Jiang et al., 2015). Zhai et al. (2009b) employed rough sets to analyse the imprecise affective responses of consumers and acquire design knowledge for improving consumer satisfaction with product design. Shi et al. (2012) used rough sets to reduce the design variables of product form design and then employed association rule mining to extract design principles. In this study, we used rough sets to extract design knowledge from Pareto optimal solutions.

This paper proposes a systematic approach to extracting design knowledge by using multiobjective optimisation and rough sets. The main contribution of this paper is the extraction of design knowledge from Pareto optimal solutions. The extracted design knowledge could be new and crucial. Furthermore, this approach only requires a few representative samples and is thus quick and incurs a low cost. The rest of this paper is structured as follows. Section 2 describes the theoretical background of the research. Section 3 presents the proposed methodology. Section 4 details a case study, whereas Section 5 discusses the results of the case study. Finally, Section 6 provides the main conclusions.

2. Theoretical background

2.1 Multiobjective optimisation

An MOP can be defined as follows: Search the decision vector \( x = [x_1, x_2, \ldots, x_n]^T \), which satisfies the \( n \) inequality constraints \( g_i(x) \leq 0, \quad \forall i = 1, 2, \ldots, n \) and the \( s \) equality constraints \( h_j(x) = 0, \quad \forall j = 1, 2, \ldots, s \), and optimises the vector of the objective function \( f(x) = [f_1(x), f_2(x), \ldots, f_r(x)]^T \) (Coello et al., 2007). Simultaneously optimising all the \( r \) objective functions by using a single solution vector \( x \) is impossible. Consequently, the logical approach involves obtaining nondominated solutions that are also called Pareto optimal solutions.

The concept of domination is defined as follows: A solution \( p \) dominates another solution \( q \) if the following two conditions are met (Deb, 2001): (1) The solution \( p \) is no worse than \( q \) in all objectives, i.e. \( f_i(p) \leq f_i(q), \quad (k = 1, 2, \ldots, r) \). (2) The solution \( p \) is strictly better than \( q \) in at least one objective, i.e. \( \exists i \in \{1, 2, \ldots, r\}, \quad f_i(p) < f_i(q) \). Based on the definition of domination, the Pareto optimality is defined as follows: A solution \( x \in \Omega \) is said “Pareto optimal” if and only if there does not exist any \( x' \in \Omega \) for which \( v = [f_1(x'), f_2(x'), \ldots, f_r(x')]^T \) dominates \( u = [f_1(x), f_2(x), \ldots, f_r(x)]^T \). Fig. 1 depicts the Pareto optimal solutions concerning an optimisation problem having two objectives (Li et al., 2019). The feasible area is inside the curve, whereas the infeasible area is outside the curve. The points given on the bold curve are Pareto optimal solutions. Therefore, the points \( A, B, C, D, E, \) and \( F \) are Pareto optimal solutions.

The multiobjective evolutionary algorithm (MEA) is a useful tool for solving MOPs (Coello et al., 2007). The improved version of the strength Pareto evolutionary algorithm (SPEA2) is a well-known MEA (Zitzler et al., 2001). It has been a benchmark MEA and successfully used to solve MOPs (Adham et al., 2015; Li et al., 2019). The SPEA2 uses a powerful diversity preservation mechanism that is based on the nearest neighbour density estimation technique. A high degree of diversity ensures a considerable variety of the obtained solutions, which can yield crucial insight regarding design possibilities (Shieh et al., 2018). Therefore, in this research, the SPEA2 was used to yield numerous Pareto optimal design solutions.
2.2 Rough sets

Rough sets are a rule-based knowledge acquisition method for studying intelligent systems characterised by inexact, uncertain, or vague information (Pawlak, 1982). Thus, rough sets are suitable for characterising the nonlinear affective responses of consumers. The lower and upper approximations are two crucial notions in rough sets. The lower approximation of $X$ refers to the maximal definable set of $X$ in $R$ and is given as follows:

$$R_-(X) = \bigcup \{ Y \in U / R : Y \subseteq X \}.$$  

(1)

The upper approximation of $X$ refers to the minimal definable set of $X$ in $R$ and is given as follows:

$$R^-(X) = \bigcup \{ Y \in U / R : Y \cap X \neq \emptyset \}.$$  

(2)

The positive region $POSR(X)$ is the positive region of $X$ in $R$, and $POSR(X) = R_-(X)$.

Rough sets employ a knowledge representation system to represent knowledge and manage uncertain data. A knowledge representation system is defined as $SU = \langle U, A, V, f \rangle$, where $U$ is the universal set; $A = C \cup D$ is the set of attributes; $C$ is the condition attribute; $D$ is the decision attribute; $V = \bigcup aV_a$, where $V_a$ indicates the domain of the attribute $a$; and $f : U \times A \rightarrow V$ is the function that indicates the attribute value of each $x$ in $U$. The dependency of the decision attribute $D$ on the condition attribute $C$ can be defined as follows (Pawlak, 1991):

$$\gamma(C, D) = \frac{\text{card}(POSR_C(D))}{\text{card}(U)}.$$  

(3)

where card(.) is the cardinality. The importance of the attribute $a$ is defined as follows (Peters et al., 2004):

$$\sigma_{(C,D)}(a) = \frac{\gamma(C, D) - \gamma(C-\{a\}, D)}{\gamma(C, D)} = 1 - \frac{\gamma(C-\{a\}, D)}{\gamma(C, D)}.$$  

(4)

When $C$ and $D$ are understood, $\sigma_{(C,D)}(a)$ is denoted by $\sigma(a)$. On the basis of the importance, the relative weight of $a$ can be calculated as follows:

$$w(a) = \frac{\sigma(a)}{\sum_{a \in C} \sigma(a)}.$$  

(5)

The reduct and core, which are used to deal with knowledge reduction in the knowledge representation system, can be defined as follows (Pawlak, 1991): Let $Q$ be independent and $\text{ind}(Q) = \text{ind}(P)$. Then, $Q \subseteq P$ is referred to as a reduct of $P$. The core of $P$ comprises all indispensable sets in $P$; therefore, if $\text{Red}(P)$ is a reduct of $P$, then $\text{Core}(P) = \bigcap \text{Red}(P)$.

The derived reducts of the knowledge representation system can be converted into decision rules. The general
structure of these rules is “IF … THEN …”, where IF denotes the antecedent, and THEN denotes the consequent. The advantage of decision rules with this structure is that these rules provide good semantic representation and are easy to interpret (Jiang et al., 2018).

3. Proposed methodology

We propose a systematic approach that integrates multiobjective optimisation and rough sets to extract knowledge for product form design related to multiple affective responses. The approach comprises three stages: (1) constructing the multiobjective optimisation model, (2) deriving the Pareto optimal solutions, and (3) extracting the design knowledge. Fig. 2 presents a flowchart of the proposed approach.

3.1 Constructing the multiobjective optimisation model
3.1.1 Design analysis

The first step of constructing the multiobjective optimisation model is design analysis, which involves analysis of the design variables and affective responses. Analysis of the design variables helps determine the nature of the product form for identifying discrete design variables (Shi et al., 2012; Shieh et al., 2017). Furthermore, morphological analysis
is adopted to decompose the product form into a set of design components. When analysing affective responses, adjectives are employed, and then factor analysis is employed to ascertain the affective factors behind these adjectives. On the basis of the affective factors, the objectives for product form design can be determined.

3.1.2 Developing the predictive models for affective responses

When the design variables and affective responses are determined, an experiment is needed so as to develop the predictive models for affective responses concerning design variables. In the experiment, representative samples must be designed. In this study, Taguchi’s orthogonal arrays are adopted to design samples. These orthogonal arrays can generate a wide range of variations and completely novel samples (Cross, 2008; Sutono et al., 2016). On the basis of experimental data, neural network can be employed to develop the predictive models that is nonlinear and is difficult to describe by using a mathematical equation (Hsiao and Huang, 2002). A back-propagation neural network has the essential features of a neural network and suitably matches product forms to consumers’ affective responses (Guo et al., 2014). Consequently, we used a back-propagation neural network to develop predictive models for affective responses.

3.1.3 Building the multiobjective optimisation model

The MOP involves optimising all of the multiple affective responses. For maximisation problem, the multiobjective optimisation model is built as follows:

$$\text{Maximize } \left[f_1(x), f_2(x), ..., f_r(x)\right]^T,$$

where $x = [x_1, x_2, ..., x_m]^T$ is a vector of the design variables and $f_k(x) (k = 1, 2, ..., r)$ is the value of affective response predicted by the back-propagation neural network.

3.2 Deriving the Pareto optimal solutions by using the SPEA2

The SPEA2 is used for solving the multiobjective optimisation model, and the following steps are employed (Li et al., 2019; Zitzler et al., 2001).

- Step 1. The first population $P(0)$ is generated, and the empty archive $A(0)$ is created with a size of $N$. The counter is set at $t = 0$.
- Step 2. The fitness values of the individuals in $P(t)$ and $A(t)$ are computed.
- Step 3. The nondominated individuals in $P(t)$ and $A(t)$ are duplicated to $A(t+1)$. If the size of $A(t+1)$ is higher than $N$, the truncation operator is adopted to decrease the size, whereas if the size of $A(t+1)$ is lower than $N$, $A(t+1)$ is filled with dominated individuals in $P(t)$ and $A(t)$.
- Step 4. Once the stopping criterion is met, the nondominated set is converted into decision vectors denoted by the nondominated individuals in $A(t+1)$, and the cycle is stopped.
- Step 5. A binary tournament selection is executed in $A(t+1)$.
- Step 6. The crossover and mutation operators are implemented, and the population $P(t+1)$ is derived. Then, increase $t$ by 1, and go to Step 2.

Because the SPEA2 is stochastic, the results obtained from only one run are not completely reliable (Durillo and Nebro, 2011). We perform numerous independent runs and then integrate the results to derive the Pareto optimal solutions in accordance with the definition of the Pareto optimality.

3.3 Extracting the design knowledge by using rough sets

Rough sets are employed to extract design knowledge from the obtained Pareto optimal solutions. The values for affective responses of the Pareto optimal solutions must be discretised. Discretisation refers to the conversion of real-valued attributes in the decision table into nominal attributes, with the discernibility between objects being maintained.

From the decision table, the importance of each design variable can be calculated using Eq. (4), and the relative
weight can be calculated using Eq. (5). Moreover, the reducts and cores of the design variables can be obtained through
the knowledge reduction described in Section 2.2. Furthermore, on the basis of the reducts, the “IF … THEN …”
decision rules can be derived.

The confidence of the decision rules extracted through the procedures proposed by Pawlak (1991) can be a value of
1, which may make the support level very low. Support is an important measure because a rule with low support may
occur only by chance and is likely to be nonessential. Thus, support is employed to eliminate uninteresting rules (Tan et
al., 2006). To derive as many as potential decision rules that satisfy minimum support and confidence thresholds from
the decision table in rough sets, association rule mining based on Apriori algorithm is employed (Shi et al., 2012).

The Apriori algorithm adopts the generate-and-test methodology to identify frequent item sets and successively
longer candidate item sets (Witten et al., 2016). For a detailed description of the Apriori algorithm, refer to Agrawal
and Srikant (1994). To strengthen the extracted rules, we introduce a minimum lift threshold. The definitions of the
support, confidence, and lift are given as follows (Han et al., 2011).

Support is equal to the number of cases for a given pair. Let $X$ be the antecedent and $Y$ be the consequent. The
support can then be defined as follows:

$$
\text{Support}(X \rightarrow Y) = P(X \cap Y).
$$

For a given pair, confidence is the ratio of the true conditions to the total possible conditions. The conditional
probability of $Y$ given $X$ is referred to as the confidence of $Y$, and thus, the confidence can be defined as follows:

$$
\text{Confidence}(X \rightarrow Y) = P(Y|X) = \frac{P(X \cap Y)}{P(X)}.
$$

Lift is a measure of the strength of occurrence of a given pair relative to random occurrence. The lift of $X$ on $Y$ can
be defined as follows:

$$
\text{Lift}(X \rightarrow Y) = \frac{P(Y|X)}{P(Y)} = \frac{P(X \cap Y)}{P(X)P(Y)}.
$$

When the lift is higher than 1, $X$ and $Y$ are positively correlated and the extracted rule is practical.

4. Case study

A car is a representative industrial product. The profile of a car has received special attention in consumer car
choice, and numerous studies have been done on this topic (Chang and Chen, 2014; Li and Zhu, 2017; Sutono et al.,
2016). Consequently, this study employed a car profile design to illustrate the proposed methodology.

4.1 Constructing the multiobjective optimisation model for car profile design
4.1.1 Design analysis for car profile design

Profile images of 120 currently available cars were selected. On the basis of these profile images, morphological
analysis was adopted to determine the design variables. There were 13 design variables that were divided into two
categories. One category concerned the form of profile parts, as detailed in Table 1, whereas the other category
concerned the ratios between different profile parts, as listed in Table 2 (Yadav et al., 2017).

A total of 60 participants (30 women and 30 men, aged 22–30 years) were recruited. These participants were
selected because they were potential consumers and usually payed more attention to car form design. The participants
were required to separate the 120 profile images of cars into 8–16 groups according to the degree of similarity in their
form. Then the combination of multidimensional scaling, hierarchical clustering technique, and K-means clustering was
used to analyse the experimental data, and 10 representative samples were obtained. For a detailed description of the
combination method, refer to Shieh et al. (2018). There were 258 adjectives collected from literature. Among them, 20
pairs of adjectives most relevant to car form design were selected using the Kawakita Jiro method. The 10
representative car samples and 20 selected pairwise adjectives were then integrated into a questionnaire based on a 7-point semantic differential scale ranging from 1 to 7. The participants were asked to complete the questionnaire. On the basis of survey results, factor analysis was adopted to explore the dimensions of these adjectives, and the results are presented in Table 3. The 20 pairs of affective adjectives were classified into four factors, and these factors accounted for 92.752% of the cumulative variance. The affective adjective pairs with the highest loading coefficients were used to name the factors (Shieh et al., 2017). Consequently, the factors were named as “Traditional–Modern”, “Uncomfortable–Comfortable”, “Orthogonal–Rounded”, and “Complex–Simple”. We took these four factors as the affective responses to establish the objectives for car form design.

| Design variables | Level 1 | Level 2 | Level 3 |
|------------------|---------|---------|---------|
| A (Front bumper) | ![Image](a.png) | ![Image](b.png) | ![Image](c.png) |
| B (Front part)   | ![Image](d.png) | ![Image](e.png) | ![Image](f.png) |
| C (Top part)     | ![Image](g.png) | ![Image](h.png) | ![Image](i.png) |
| D (Rear part)    | ![Image](j.png) | ![Image](k.png) | ![Image](l.png) |
| E (Rear bumper)  | ![Image](m.png) | ![Image](n.png) | ![Image](o.png) |

4.1.2 Developing the predictive models for affective responses

Design samples were required to develop the predictive models for affective responses concerning design variables. The 13 design variables could generate $1,594,323$ ($3^{13}=1,594,323$) possible design samples, which was too many for performing the experiment. In order to decrease the number of samples, Taguchi’s $L_{27}(3^{13})$ orthogonal array was employed, and 27 samples were generated, as presented in Fig. 3 and Table 4. A questionnaire was constructed by integrating the 27 samples with the four affective responses through the 7-point (1–7) semantic differential scale. After that, an evaluation was carried out using the questionnaire in an industrial design laboratory. A total of 32 participants (16 women and 16 men, aged 22–30 years) were invited to evaluate the 27 samples in random order. The experimental results are presented in Table 5.

On the basis of the experimental data, predictive models were established using the back-propagation neural network. A detailed description of predictive model establishment can be found in Chen and Chang (2014). By using the predictive models, the affective response values $f_{\text{Traditional–Modern}}(x)$, $f_{\text{Uncomfortable–Comfortable}}(x)$, $f_{\text{Orthogonal–Rounded}}(x)$, and $f_{\text{Complex–Simple}}(x)$ were predicted from the vector of the design variable values $[x_1, x_2, x_3, \ldots, x_{13}]$. 
Table 2  Design variables for car ratio.

| Design variables | Diagrammatic sketch | Level 1 | Level 2 | Level 3 |
|------------------|---------------------|--------|--------|--------|
| F (Ratio of car height to car length, $H_1/L_1$) | ![Diagram](image1) | 0.32   | 0.37   | 0.42   |
| G (Ratio of car top part to car height, $H_2/H_1$) | ![Diagram](image2) | 0.27   | 0.30   | 0.33   |
| H (Ratio of wheel height to car height, $H_3/H_1$) | ![Diagram](image3) | 0.40   | 0.45   | 0.50   |
| I (Ratio of chassis height to wheel height, $H_4/H_3$) | ![Diagram](image4) | 0.20   | 0.35   | 0.50   |
| J (Ratio of fore part length to car length, $L_2/L_1$) | ![Diagram](image5) | 0.18   | 0.24   | 0.30   |
| K (Ratio of rear part length to car length, $L_3/L_1$) | ![Diagram](image6) | 0.09   | 0.13   | 0.17   |
| L (Ratio of front overhang length to car length, $L_4/L_1$) | ![Diagram](image7) | 0.14   | 0.18   | 0.22   |
| M (Ratio of rear overhang length to car length, $L_5/L_1$) | ![Diagram](image8) | 0.17   | 0.20   | 0.23   |

4.1.3 Building the multiobjective optimisation model for car profile design

Maximising the semantic differential scale is essential for deriving a design with a right-sided affective response, whereas when deriving a design with a left-sided affective response, the semantic differential scale must be minimised. In this study, the participants were invited to express their preferences related to the four affective responses. The results suggested they needed a car which appeared “Modern”, “Comfortable”, “Rounded”, and “Simple”. These affective responses were all right-sided; thus, the multiobjective optimisation model was built as follows:

$$
\begin{align*}
\text{Maximize } & f_{\text{Traditional–Modern}}(x), \\
\text{Maximize } & f_{\text{Uncomfortable–Comfortable}}(x), \\
\text{Maximize } & f_{\text{Orthogonal–Rounded}}(x), \\
\text{Maximize } & f_{\text{Complex–Simple}}(x), \\
\text{Subject to } & x = [x_1, x_2, ..., x_{13}]^T, \\
& x_i = \{1, 2, 3\}, \forall i = 1, 2, ..., 13.
\end{align*}
$$

(10)
Table 3  Factor loadings of 20 pairs of affective adjectives using four factors.

| Pairs of affective adjectives | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
|-------------------------------|----------|----------|----------|----------|
| Traditional–Modern            | 0.956    | 0.108    | 0.096    | 0.032    |
| Common–Exclusive              | 0.946    | 0.257    | -0.048   | -0.022   |
| Usual–High-tech               | 0.938    | 0.293    | 0.065    | 0.037    |
| Static–Dynamic                | 0.920    | -0.034   | 0.143    | -0.001   |
| Nostalgic–Avant-garde         | 0.900    | 0.396    | 0.069    | 0.026    |
| Straight–Streamlined          | 0.862    | 0.308    | 0.196    | -0.121   |
| Cheap–Expensive               | 0.801    | 0.545    | -0.132   | -0.054   |
| Calming–Exciting              | 0.688    | 0.618    | 0.004    | 0.130    |
| Dull–Vivid                    | 0.667    | -0.327   | 0.622    | 0.013    |
| Coarse–Delicate               | 0.656    | 0.652    | 0.264    | 0.128    |
| Uncomfortable–Comfortable     | 0.104    | 0.943    | -0.229   | 0.018    |
| Awkward–Elegant               | 0.404    | 0.902    | 0.063    | 0.069    |
| Ugly–Beautiful                | 0.417    | 0.874    | 0.083    | 0.121    |
| Fragile–Strong                | 0.224    | 0.854    | -0.333   | 0.253    |
| Light–Heavy                   | -0.297   | 0.829    | -0.341   | 0.247    |
| Plain–Luxurious               | 0.619    | 0.766    | 0.074    | 0.030    |
| Somber–Delightful             | 0.614    | 0.723    | 0.245    | 0.118    |
| Orthogonal–Rounded            | 0.102    | -0.075   | 0.890    | 0.015    |
| Complex–Simple                | -0.060   | 0.127    | 0.309    | 0.837    |
| Feminine–Masculine            | 0.055    | 0.220    | -0.339   | 0.834    |

Final statistics

|                  | Eigenvalue | Percentage of variance | Cumulative percentage |
|------------------|------------|------------------------|-----------------------|
|                  | 8.340      | 41.699                 | 41.699                |
|                  | 6.690      | 33.450                 | 75.148                |
|                  | 1.911      | 9.557                  | 84.706                |
|                  | 1.609      | 8.046                  | 92.752                |

The bold numbers indicate the categories of affective adjectives associates with factors 1–4.

Fig. 3 The 27 experimental samples.
Table 4  Experimental samples determined using the $L_{27}(3^{13})$ orthogonal array.

| Experimental sample No. | Level of design variables |
|-------------------------|---------------------------|
|                         | A | B | C | D | E | F | G | H | I | J | K | L | M |
| 1                       | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2                       | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3                       | 1 | 1 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 4                       | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| 5                       | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 |
| 6                       | 1 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 7                       | 1 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 3 | 2 | 2 | 2 |
| 8                       | 1 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 | 3 | 3 | 3 |
| 9                       | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 |
| 10                      | 2 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 11                      | 2 | 1 | 2 | 3 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 |
| 12                      | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 |
| 13                      | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 2 | 3 | 1 | 3 | 1 | 2 |
| 14                      | 2 | 2 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 |
| 15                      | 2 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 1 |
| 16                      | 2 | 3 | 1 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 2 | 3 | 1 |
| 17                      | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 3 | 1 | 2 |
| 18                      | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 |
| 19                      | 3 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 |
| 20                      | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 |
| 21                      | 3 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 |
| 22                      | 3 | 2 | 1 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 3 | 2 | 1 |
| 23                      | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 |
| 24                      | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 2 | 1 | 3 |
| 25                      | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 3 | 2 | 1 | 2 | 1 | 3 |
| 26                      | 3 | 3 | 2 | 1 | 2 | 1 | 3 | 1 | 3 | 2 | 3 | 2 | 1 |
| 27                      | 3 | 3 | 2 | 1 | 3 | 2 | 1 | 2 | 1 | 3 | 1 | 3 | 2 |

4.2 Deriving the Pareto optimal solutions for car profile design

The SPEA2 were employed to solve the multiobjective optimisation model. The corresponding parameters were as follows: generation number 25 000, population size 100, crossover rate 0.80, and mutation rate 0.20. We executed 30 independent runs for this MOP. The solutions from 30 independent runs were integrated, and 151 Pareto optimal solutions were obtained. These solutions were divided into four clusters by using fuzzy c-means clustering algorithm (Bezdek et al., 1984), as shown in Fig. 4. The representative Pareto optimal solutions closest to each cluster centre are illustrated in Fig. 5.

4.3 Extracting the design knowledge for car profile design

To obtain the decision table of rough sets, the values of the affective responses of the 151 Pareto solutions were discretised into three categories: bottom-2-box, that is, [1, 3], classified as level 1; middle-2-box, that is, (3, 5), classified as level 2; and top-2-box, that is, [5, 7], classified as level 3 (Albert and Tullis, 2013). Consequently, the decision table was obtained, as presented in Table 6.
(ratio of rear overhang length to car length) influenced the affective response of the “Complex–Simple”, and the design variable E had the strongest effect on the affective response of “Complex–Simple”, followed by F, B, I, J, and M.

Table 5  Evaluation results for the affective responses.

| Experimental sample No. | Traditional–Modern | Uncomfortable–Comfortable | Orthogonal–Rounded | Complex–Simple |
|-------------------------|--------------------|---------------------------|--------------------|---------------|
| 1                       | 4.492              | 4.875                     | 2.398              | 3.515         |
| 2                       | 4.145              | 4.302                     | 3.077              | 3.621         |
| 3                       | 2.370              | 2.732                     | 2.495              | 4.470         |
| 4                       | 4.895              | 4.472                     | 3.854              | 4.046         |
| 5                       | 4.840              | 4.684                     | 4.475              | 4.549         |
| 6                       | 3.120              | 4.366                     | 5.484              | 4.364         |
| 7                       | 5.919              | 4.429                     | 4.824              | 6.060         |
| 8                       | 4.950              | 4.175                     | 6.280              | 6.007         |
| 9                       | 4.492              | 4.790                     | 6.202              | 5.689         |
| 10                      | 5.206              | 5.087                     | 4.319              | 4.841         |
| 11                      | 3.559              | 4.175                     | 4.436              | 3.887         |
| 12                      | 4.767              | 4.684                     | 4.358              | 5.026         |
| 13                      | 4.456              | 4.472                     | 4.979              | 4.284         |
| 14                      | 3.248              | 4.260                     | 5.814              | 3.436         |
| 15                      | 5.919              | 5.023                     | 4.727              | 5.291         |
| 16                      | 3.889              | 3.920                     | 2.320              | 3.568         |
| 17                      | 2.919              | 2.690                     | 2.747              | 2.720         |
| 18                      | 4.858              | 3.942                     | 3.427              | 4.814         |
| 19                      | 4.163              | 5.278                     | 5.756              | 5.689         |
| 20                      | 6.340              | 5.490                     | 5.698              | 6.034         |
| 21                      | 3.504              | 2.987                     | 4.164              | 4.523         |
| 22                      | 3.120              | 3.687                     | 3.058              | 4.470         |
| 23                      | 4.748              | 4.451                     | 3.446              | 4.072         |
| 24                      | 4.767              | 4.408                     | 4.009              | 5.742         |
| 25                      | 3.449              | 4.175                     | 4.844              | 4.841         |
| 26                      | 5.480              | 4.302                     | 3.873              | 5.795         |
| 27                      | 4.767              | 4.832                     | 4.649              | 5.662         |

Fig. 4 Pareto optimal front in objective space for (a) the “Traditional–Modern” and “Uncomfortable–Comfortable” affective responses and (b) the “Orthogonal–Rounded” and “Complex–Simple” affective responses.
Fig. 5 Representative Pareto optimal solutions for (a) cluster 1, (b) cluster 2, (c) cluster 3, and (d) cluster 4.

Table 6 Decision table based on the Pareto optimal solutions.

| No.  | X1  | X2  | X3  | X4  | X5  | X6  | X7  | X8  | X9  | X10 | X11 | X12 | X13 | AR1 | AR2 | AR3 | AR4 |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1    | 3   | 2   | 3   | 3   | 1   | 1   | 2   | 1   | 1   | 2   | 1   | 1   | 2   | 3   | 3   | 3   | 3   |
| 2    | 3   | 2   | 3   | 3   | 2   | 1   | 1   | 2   | 1   | 1   | 1   | 2   | 2   | 2   | 2   | 2   | 2   |
| 3    | 3   | 3   | 3   | 3   | 2   | 1   | 3   | 3   | 2   | 1   | 3   | 3   | 3   | 3   | 3   | 3   | 3   |
| ⋮    | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   | ⋮   |
| 151  | 3   | 3   | 3   | 3   | 2   | 1   | 2   | 1   | 3   | 1   | 1   | 1   | 3   | 3   | 3   | 3   | 3   |

AR1, AR2, AR3, and AR4 represent “Traditional–Modern”, “Uncomfortable–Comfortable”, “Orthogonal–Rounded”, “Complex–Simple”, respectively.

Table 7 Relative weights of the design variables for the affective responses.

| Affective Response | A    | B    | C    | D    | E    | F    | G    | H    | I    | J    | K    | L    | M    |
|--------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| AR1                | 0    | 0.026| 0    | 0    | 0.026| 0.922| 0    | 0    | 0    | 0.026| 0    | 0    | 0    |
| AR2                | 0    | 0.168| 0    | 0    | 0.123| 0.297| 0    | 0    | 0.103| 0.129| 0.103| 0.064| 0.013|
| AR3                | 0    | 0.198| 0    | 0    | 0.364| 0    | 0    | 0    | 0.176| 0.131| 0.043| 0.022| 0.066|
| AR4                | 0    | 0.217| 0    | 0    | 0.348| 0.306| 0    | 0    | 0.043| 0.043| 0    | 0    | 0.043|

AR1, AR2, AR3, and AR4 represent “Traditional–Modern”, “Uncomfortable–Comfortable”, “Orthogonal–Rounded”, “Complex–Simple”, respectively.

The reducts and cores of the design variables were derived and are presented in Table 8. From the results, the important design variables for the affective responses could be identified. For example, for the affective response of “Traditional–Modern”, the important design variables were B, E, F, and J; moreover, the design variables B, E, and J were important to all four affective responses.

Table 8 Reducts and cores of the design variables for the affective responses.

| Affective Response       | Reduct | Core   |
|--------------------------|--------|--------|
| Traditional–Modern       | B E F J| B E F J|
| Uncomfortable–Comfortable| B E F I J K L M| B E F I J K L M|
| Orthogonal–Rounded       | B E I J K L M| B E I J K L M|
| Complex–Simple           | B E F I J M| B E F I J M|

To extract decision rules, we set the minimum support as 0.300, minimum confidence as 0.950, and minimum lift as 1.000. The decision rules concerning all four affective responses can be derived, as shown in Tables 9–12. These rules can provide design principles for car profile design. For example, one of the rules concerning the affective response of “Traditional–Modern” is as follows: if F = 1 (i.e., the ratio of car height to car length is 0.32), then the classified level of the “Traditional–Modern” is 3 (see Table 9).

5. Discussion

A systematic approach is proposed for extracting design knowledge by using multiobjective optimisation and rough sets. Multiobjective optimisation is employed to generate Pareto optimal solutions, whereas rough sets are used to extract design knowledge from the knowledge representation system, which is composed of the Pareto optimal design variables and corresponding affective responses. Thus, the proposed approach extracts design knowledge from
optimised solutions, and therefore, the extracted knowledge is common to the optimal solutions and could be new and crucial (Deb and Srinivasan, 2006).

Table 9  Decision rules for the affective response of “Traditional–Modern”.

| Rule | IF     | THEN         | Support | Confidence | Lift   |
|------|--------|--------------|---------|------------|--------|
| 1    | – – 1  | 3            | 0.682   | 1.000      | 1.238  |
| 2    | – – 1  | 2            | 0.338   | 1.000      | 1.238  |
| 3    | 3 – 1  | 3            | 0.305   | 1.000      | 1.238  |
| 4    | – – 1  | 3            | 0.305   | 1.000      | 1.238  |

Table 10  Decision rules for the affective response of “Uncomfortable–Comfortable”.

| Rule | IF     | THEN         | Support | Confidence | Lift   |
|------|--------|--------------|---------|------------|--------|
| 1    | – – 1  | 3            | 0.338   | 0.981      | 1.410  |
| 2    | – – 1  | 1            | 0.318   | 0.951      | 1.354  |
| 3    | – – 1  | 1            | 0.384   | 0.961      | 1.367  |

Table 11  Decision rules for the affective response of “Orthogonal–Rounded”.

| Rule | IF     | THEN         | Support | Confidence | Lift   |
|------|--------|--------------|---------|------------|--------|
| 1    | – – 1  | 2            | 0.338   | 0.981      | 1.114  |
| 2    | – 3 –  | 3            | 0.397   | 0.984      | 1.117  |
| 3    | – 3 –  | 3            | 0.331   | 1.000      | 1.135  |
| 4    | – 3 –  | 1            | 0.351   | 0.981      | 1.114  |
| 5    | – 3 –  | 1            | 0.344   | 0.981      | 1.114  |

Table 12  Decision rules for the affective response of “Complex–Simple”.

| Rule | IF     | THEN         | Support | Confidence | Lift   |
|------|--------|--------------|---------|------------|--------|
| 1    | – – 1  | 3            | 0.682   | 1.000      | 1.056  |
| 2    | 3 – 3  | 3            | 0.464   | 1.000      | 1.056  |
| 3    | 3 – 3  | 3            | 0.430   | 1.000      | 1.056  |
| 4    | 3 – 3  | 3            | 0.377   | 1.000      | 1.056  |
| 5    | 3 – 3  | 3            | 0.503   | 1.000      | 1.056  |
| 6    | 3 – 3  | 3            | 0.351   | 1.000      | 1.056  |
| 7    | 3 – 3  | 3            | 0.404   | 1.000      | 1.056  |

In the case study for car profile design, the experimental samples were determined by using Taguchi’s orthogonal array. These samples were extremely representative, and a few samples exhibited poor affective responses. Among the 27 experimental samples, only 5 satisfied Pareto optimality (i.e., samples No. 7, No. 8, No. 9, No. 19, and No. 20). There were 13 design variables, and the number of design variables could not be further reduced via the 27 experimental samples or the 5 Pareto samples; in other words, no reducts and cores were obtained using rough sets in this situation.

We used 27 representative samples to construct the multiobjective optimisation model, and 151 Pareto optimal solutions were generated. Employing these Pareto optimal solutions, the design variables were reduced by using rough sets for dealing with the nonlinear affective responses of consumers to products (Chien et al., 2014). On the basis of the reducts, the design rules concerning the design variables and affective responses could be determined. Thus, we extracted design knowledge that was common to the Pareto optimal solutions by using only a few representative samples. That is to say, the proposed approach can obtain design knowledge within a short time and at a low cost.
We employed the Apriori algorithm, which is a generate-and-test method, for extracting design rules (Shi et al., 2012). To ensure the reliability of the rules, we introduced three evaluation indices: support, confidence, and lift. The larger the support, confidence, and lift, the stronger the rule. When the thresholds for the minimum support, confidence, and lift were large, the number of rules was low. To identify which rules are most crucial, designers can set larger thresholds for the minimum support, confidence, and lift. The extracted design principles can provide design insight; however, no in-depth study has been conducted on the cause–effect relationship between design variables and affective responses. Future studies could focus on the internal mechanism of these design rules.

To extract design knowledge using the traditional method which employs numerous representative design samples collected from the market (Nagamachi et al., 2006), we asked the participants to evaluate the four affective responses concerning the profile images of 120 currently available cars mentioned in Section 4.1.1. On the basis of the evaluation result, the reducts and cores of the design variables for the affective responses were extracted, as shown in Table 13. Obviously, the reducts obtained using the proposed method contain the reducts obtained using the traditional method, and the cores obtained using the proposed method also contain the cores obtained using the traditional method. Furthermore, no decision rules were extracted through the traditional method when using the thresholds employed in the proposed method (i.e., minimum support = 0.300, minimum confidence = 0.950, and minimum lift = 1.000). The reason could be that the samples used in the traditional method were representative and there were few common combination models of design variables among these samples; by contrast, the samples used in the proposed method were all Pareto solutions and there were some common combination models. Clearly, the proposed method can generate more cores and reducts, and thus can derive more crucial decision rules. Note that there may exist interaction effect among the design variables, and it was not considered in this study. Additional studies could focus on such interaction effect when extracting design knowledge more precisely by using the proposed approach.

Table 13  Reducts and cores obtained using the traditional method.

| Affective response        | Reduct | Core |
|---------------------------|--------|------|
| Traditional–Modern        | B E    | B E  |
| Uncomfortable–Comfortable | B E F I| B E F I|
| Orthogonal–Rounded        | B E J K| B E J K|
| Complex–Simple            | B E F  | B E F |

Although a car profile was employed as a case study, the proposed approach can be used to other products, such as mobile phones (Jiang Kwong Siu et al., 2015), drip coffee makers (Hsiao et al., 2010), and digital cameras (Guo et al., 2014). When using the proposed approach to other products, the multiobjective optimisation model should first be constructed; the Pareto solutions should be generated using the SPEA2; finally, design knowledge should be extracted using rough sets. The proposed approach is somewhat complicated and consists of various technologies. However, it is suitably implemented for extracting design knowledge. Moreover, the approach incorporates three simplification stages, which balance the complexity of the approach. Therefore, the proposed methodology can be universally used to extract design knowledge.

6. Conclusion

In this paper, a knowledge extraction approach for product form design has been proposed by combining multiobjective optimisation and rough sets. Multiobjective optimisation is employed to generate numerous Pareto optimal solutions. Rough sets are then used to extract design knowledge from these Pareto optimal solutions. A car profile design was adopted to illustrate the approach. The results suggest that the approach extracts useful design knowledge, such as relative weights, reducts and cores, and design rules concerning the design variables and affective responses. The proposed approach extracts design knowledge from the Pareto optimal solutions. This knowledge may be new and crucial and thus provide substantial design insight. Furthermore, this approach requires only a few representative experimental samples, and thus, it is time- and cost-efficient.

In this study, the affective responses were treated separately, and the design knowledge corresponding to each affective response was extracted. The design knowledge for the integrated affective responses was not extracted. Future research could focus on studying the preferences of consumers, integrating multiple affective responses into a single
comprehensive index based on the preference, and extracting design knowledge by using the comprehensive index.

Acknowledgements

This study is supported by the Philosophy and Social Sciences Fund Project of Jiangsu Higher Education Institutions, China (Project No. 2019SJA0930), and the Research Fund Project of Jiangsu Normal University, China (Project No. 18XWRX031). The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their valuable comments and suggestions.

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