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A quantitative approach to design alternative evaluation based on data-driven performance prediction

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ABSTRACT

Design alternative evaluation in the early stages of engineering design plays an important role in determining the success of new product development, as it influences considerably the subsequent design activities. However, existing approaches to design alternative evaluation are overly reliant on experts' ambiguous and subjective judgments and qualitative descriptions. To reduce subjectivity and improve efficiency of the evaluation process, this paper proposes a quantitative evaluation approach through data-driven performance predictions. In this approach, the weights of performance characteristics are determined based on quantitative assessment of expert judgments, and the ranking of design alternatives is achieved by predicting performance values based on historical product design data. The experts' subjective and often vague judgments are captured quantitatively through a rough number based Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. In order to facilitate performance based quantitative ranking of alternatives at the early stages of design where no performance calculation is possible, a particle swarm optimization based support vector machine (PSO-SVM) is applied for historical data based performance prediction. The final ranking of alternatives given the predicted values of multiple performance characteristics is achieved through Višekriterijumska Optimizacija I kompromisno Rešenje (VIKOR). A case study is carried out to demonstrate the validity of the proposed approach.
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1. Introduction

Design alternative evaluation in the early stage of engineering design is a process by which newly generated design alternatives are evaluated according to various criteria and the best one is selected [1]. It is a critical design activity in new product development (NPD) with considerable impact on the quality, cost, and desirability of the end product. Successful design alternative evaluation can often reduce high redesign costs and development time during the later stages of the NPD [2]. Evaluation of design alternatives is a multi-criteria decision making (MCDM) process involving many complex factors. In most previous evaluation frameworks, criterion weight determination and design alternative ranking both rely heavily on subjective judgments and qualitative descriptions by design experts [3–6]. Results are often unavoidably tendentious and potentially ineffective. It is thus not sufficient to consider only expert opinions when evaluating new product alternatives. Adequate supplementary information is needed.

When developing new products, many companies generate different design alternatives by modifying and improving various function modules in a product family in order to meet diverse customer needs [7]. Design alternatives within a product family share some similar performance, which has a direct effect on the purchase behaviors of customers [8]. Performance characteristics are the engineering description of customer needs and understandable to designers. Therefore, to respond to dynamic market promptly and ensure the success of NPD, it is essential to evaluate design alternatives according to performance characteristics. In this paper, performance characteristics represent quantitative evaluation criteria.

When determining the weight of each criterion, i.e., performance characteristic, the complex interactions and dependencies among evaluation criteria are difficult for experts to assess, yet these relationships can have significant influences on the weights of criteria [9–11]. Thus, an effective tool is needed to analyze the mutual relationship among criteria so that experts' qualitative judgments on the weights can be captured more effectively. Besides, the judgments of decision makers are usually ambiguous and uncertain due to lack of precision and confidence levels at the early stage of engineering design [12]. It is vital to analyze

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those judgments using proper mechanisms to obtain more adequate weights. Therefore, the quest for effective and quantitative methodologies to determine the weights of performance characteristics is a key issue.

Design information is often vague, incomplete and inconsistent at early design stages. Thus, most existing approaches apply subjective and qualitative evaluation of experts to identify optimal design alternatives. For example, in the case a weighted concept selection matrix method is used [13,14], a group of experts are required to fill in the cells of the matrix with subjective numbers often through brainstorming sessions. Although this way works, seniority and inconsistent composition of the evaluation team can sometimes lead to highly variable and discordant evaluation results. How to reduce the subjective bias of human involvement and increase efficiency in ranking and selection of design alternatives has been a challenge among researchers.

After generating design alternatives, the engineering specifications of each alternative are determined by tools and techniques, such as Quality Function Deployment (QFD), but the performance of each design alternative is not easy to obtain beforehand. Under this circumstance, experts have to make their vague and subjective judgments or estimations about the performance of each design alternative. Therefore, the selected optimal one would be inconsistent and in poor quality. If the complex nonlinear relationship between engineering specifications and performance characteristics can be established using mathematical methods, it is possible to reduce the influence of subjective factors by estimating the values of performance characteristics of each alternative in advance. Although no analytical model exists to calculate values of performance characteristics for a given alternative because of the limitation of available information at the early stages of design, the historical product family design data can be analyzed to generate useful predictions. Through data mining and regression analysis, we can construct performance prediction models which can be applied to forecast values of performance characteristics for each design alternative. Then, the alternatives can be ranked by values of performance characteristics to assist decision makers in selecting the optimal alternative. As a result, the evaluation process can be more objective and efficient.

In this paper, we propose a systematic approach, based on performance prediction, to quantitatively evaluate the design alternatives of a modular product. This involves two procedures: quantifying expert judgments on performance characteristic weights and data-driven performance prediction for alternative ranking. Rough number combined with Decision-Making Trial and Evaluation Laboratory (rough DEMATEL) is proposed to quantify expert judgments to determine weights in subjective environment. Particle swarm optimization based support vector machine (PSO-SVM) and Višekriterijumska Optimizacija I kompromisno Rešenje (VIKOR) are proposed to objectively and efficiently rank design alternatives based on the predictive values of performance characteristics. The rest of this paper is organized as follows. Section 2 presents a brief review of the related work. In Section 3, the quantitative approach to design alternative evaluation based on data-driven performance prediction is proposed. In Section 4, a case study is presented. Section 5 draws the conclusion.

2. Literature review

In the early stage of new product development, most of information is ambiguous, imprecise, and inconsistent. Therefore, criterion weights have to be determined subjectively by decision-makers. For the purpose of capturing and expressing the true perceptions of decision-makers efficiently and accurately in the uncertain environment, fuzzy set was introduced by many researchers to deal with these issues [10,14–16]. However, the performance of the fuzzy set is deeply dependent on the selection of membership functions. Contrary to fuzzy set theory, rough number, which is based on rough set theory [17], is an efficient mathematical tool to handle ambiguous and imprecise problems, and express vagueness merely depending on the original data without using any auxiliary information or additional subjective judgments [18]. The rough number usually involves lower and upper limits that represent rough boundary interval. In this regard, it can offer a more impersonal result of the decision problem in the evaluation process. Contemporarily, the rough number is widely used in design concept evaluation [3–5]. Even though rough number can effectively deal with subjectivity and vagueness in the decision-making process, there lacks an effective evaluation framework to manage alternatives in relation to many criteria. Traditional evaluation frameworks, such as Analytic Hierarchy Process (AHP), which assume that the criteria are independent, cannot deal with complex interactions and dependencies among criteria [19]. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) was firstly put forward by the Geneva Research Centre of the Battelle Memorial Institute [20]. The method is based on graph theory and conducive to help visualize the structure of complicated causal relationships and the importance of influence between factors. DEMATEL have been combined with fuzzy set theory to solve the MCDM problems [21,22]. However, there are few in the literature of combining DEMATEL with rough number to determine criterion weights.

Many methods have been applied by experts to rank design alternatives in qualitative ways, such as Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [5,23,24], VIKOR [10,25–27], ELimination Et Choix Traduisant la Realité (ELECTRE) [28,29], multi-attribute utility theory (MAUT) [30,31], Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) [32,33] and so forth. Due to the insufficient, inaccurate, ambiguous or even discordant information available for design alternative evaluation, it is inevitable that the evaluation result is imprecise and partial. The evaluation models based on data mining techniques are emerging, and the main objective of such models is to achieve a more scientific and reliable evaluation result [34–38].

More attention has recently been paid to the artificial neural network (ANN) to build nonlinear prediction models to aid evaluation [39–41]. Nevertheless, in order to ensure prediction accuracy, ANN demands a large amount of data for training. Support vector machine (SVM), firstly introduced by Vapnik [42,43], is regarded as one of prediction techniques for settling problems with the characters of small samples, nonlinearity, high dimension and local minimal points. Compared with ANN, which tries to minimize the error on the training data, SVM focuses on the global optimum and reveals better prediction accuracy owing to its implementation of structural risk minimization principle, seeking to minimize an upper bound of the generalization error [44]. SVM has offered many promising prediction results in product design [45–47], product demand [48,49], and stock market [50,51]. Several hyper-parameters of SVM have strong impacts on forecast accuracy. Hence, it is essential to select a search algorithm to seek the optimal hyper-parameter combination. Particle swarm optimization (PSO), which was proposed by Kennedy and Eberhart [52], is a population-based search algorithm inspired by social interaction and communication of bird flocking or fish schooling, and regarded as an excellent technique to solve combinatorial optimization problems. Compared with other search algorithm, such as grid search (GS) [53] and genetic algorithm (GA) [50,54], PSO possesses the extensive ability of easy adjustment, global optimization and fast convergence. Therefore, PSO-SVM has been widely applied by many researchers [55–57], and it has been proved to have prominent forecasting performance.

The VIKOR method was first put forth by Opricovic [58]. It is an applicable technique to rank and select multiple alternatives under conflicting criteria. When each alternative is evaluated according to multi-criteria, VIKOR introduces a ranking index based on measuring the "closeness" to the "ideal" alternative [59]. In the recent literature, many methods have combined with VIKOR for qualitatively ranking and selecting alternatives. Based on rough number, Zhu et al. [4] proposed an integrated AHP and VIKOR for evaluation of design alternatives. Tadić et al. [10] put forward a novel hybrid MCDM model based on fuzzy DEMATEL, fuzzy ANP and fuzzy VIKOR for city logistics concept selection. Zandi and Roghanian [28] proposed a combination of Fuzzy ELECTRE and VIKOR method for selecting an optimal site to build a new plant.

Among various decision-making techniques, rough number is utilized to solve the deficiencies in fuzzy concept evaluation approach, such as fuzzy AHP. Meanwhile, DEMATEL has superior competence to AHP. To manipulate the subjectivity in weight determination of evaluation criteria, we intend to start by applying the rough DEMATEL method. Data mining technique, PSO-SVM, is applied to reduce the subjectivity and imprecision during evaluation. Meanwhile, VIKOR is proved as a powerful alternative ranking framework. To perform design alternative ranking, we then try to use the integrated method, PSO-SVM-VIKOR. In sum, the proposed method which combines the merit of above techniques aims at finding: an improved solution to enhance the efficiency and objectivity of decision-making in design alternative evaluation. In this respect, this paper focus on meeting designers' practical needs for decision-making support rather than only intending to develop an integrated method.

3. Proposed method

3.1. Framework of the proposed method

Design alternative evaluation is a complicated multi-criteria decision-making problem, consisting of two stages: determination of criterion weights and ranking of alternatives. The goal of design alternative evaluation is to rank and select the optimal alternative according to the comprehensive evaluation value. The comprehensive evaluation value of an alternative can be calculate as below:

$$Eval(A_i) = f(\varphi(w_1, p_{11}), \varphi(w_j, p_{ij}), \ldots, \varphi(w_n, p_{mn})) \quad (1)$$

where A_i represents the ith alternative, w_j represents the weight of jth criterion, p_{ij} represents the evaluation value of A_i under the jth criterion, $\varphi(w_j, p_{ij})$ represents the weighted evaluation value of A_i under the jth criterion, f indicates the method or function to synthesize the weighted evaluation values of A_i under all criteria.

In the stage of the criterion weight determination, the mutual influence relationships among criteria, which are identified by experts, crucially influence the determination of criterion weights. Currently this influence is counted by the experts in their assessment of the weight of each criterion (w_j), possibly leading to subjectively biased weights. Furthermore, the inconsistency and vagueness inherently involved in the subjective weight assessment process can also be a problem. Therefore, a quantitative method is needed to make the weight determination process more objective; in the alternative ranking stage, generally, alternative ranking relies on qualitative evaluation by experts. Due to subjective preferences and limitations of knowledge and experience, the evaluation value (p_{ij}) of the same design alternative A_i may differ considerably. As a result, an unreasonable optimal alternative could be obtained. Furthermore, the lack of systematic methods to obtain weighted evaluation value $\varphi(w_j, p_{ij})$ and a method or function f to synthesize the weighted evaluation values may lead to longer time for ranking alternatives, especially when the number of criteria and alternatives are large. How to enhance the objectivity and efficiency in obtaining the evaluation values of design alternatives is a key issue.

To solve these problems, this paper proposes a quantitative design alternative evaluation method based on data-driven performance prediction. Performance characteristics are evaluation criteria obtained from expert opinions. Rough DEMATEL is adopted to quantitatively analyze mutually influencing relationships between performance characteristics, and handle inconsistent and vague judgments from experts, leading to better estimate of the weights of evaluation criteria. Historical product family data, which includes engineering specification values and performance characteristic values of different modular products in the same product family, are collected. PSO-SVM is used to construct prediction models for each performance characteristic by analyzing the historical data. Engineering specifications which have high correlation with each performance characteristic are chosen as input variables of perdition models to forecast values of performance characteristics for each design alternative. If all performance characteristics are benefit or cost criteria, weighted averaging operator [60] is adopted to rank the alternatives based on predictive values of performance characteristics. If not, VIKOR is adopted. Thus, the proposed method quantifies the influence of experts on the weights of evaluation criteria, and evaluates design alternatives based on data-driven performance prediction. The framework of the proposed method is presented in Fig. 1.

3.2. Quantifying expert judgments on performance characteristic weights

As the determination of performance characteristic weights usually requires professional knowledge and experience, judgments of design experts are essential in this process. In addition, vagueness and uncertainty in the expert judgments should be quantitatively measured to gain more accurate and objective weights of performance characteristics.

Various methods have been developed to compare each criterion with other criteria for identifying their relative importance in the light of expert judgments, such as AHP. However, it is hard for experts to apply AHP to evaluate one criterion when it has interdependent relationships with the others and identify its weak or strong influence to the others. Usually, there are mutual influence relationships among performance characteristics. For example, the cost of a product may affect its lifetime and quality in different degree, and these relationships have considerable impact on criterion weights. The influence degree of a performance characteristic to the others can reflect its relative weight. DEMATEL is an effective evaluation framework for exploring interrelated and nonlinear relationships between criteria by computing the total and net directional influence [61–63]. Experts can utilize this tool to judge the mutual influence relationships among performance characteristics based on their domain knowledge and experience, then obtain the weights of them. To solve the ambiguity and uncertainty in the subjective judgments of experts, rough number is applied to offer more impersonal results. Although these methods have been implemented in the literature, few researchers combine these two methods together. In this section, rough DEMATEL is proposed to quantitatively determine the weight of performance characteristics, considering mutual influence relationships. The steps of the rough DEMATEL method are as follows:

(1) Collect information and knowledge about performance characteristics

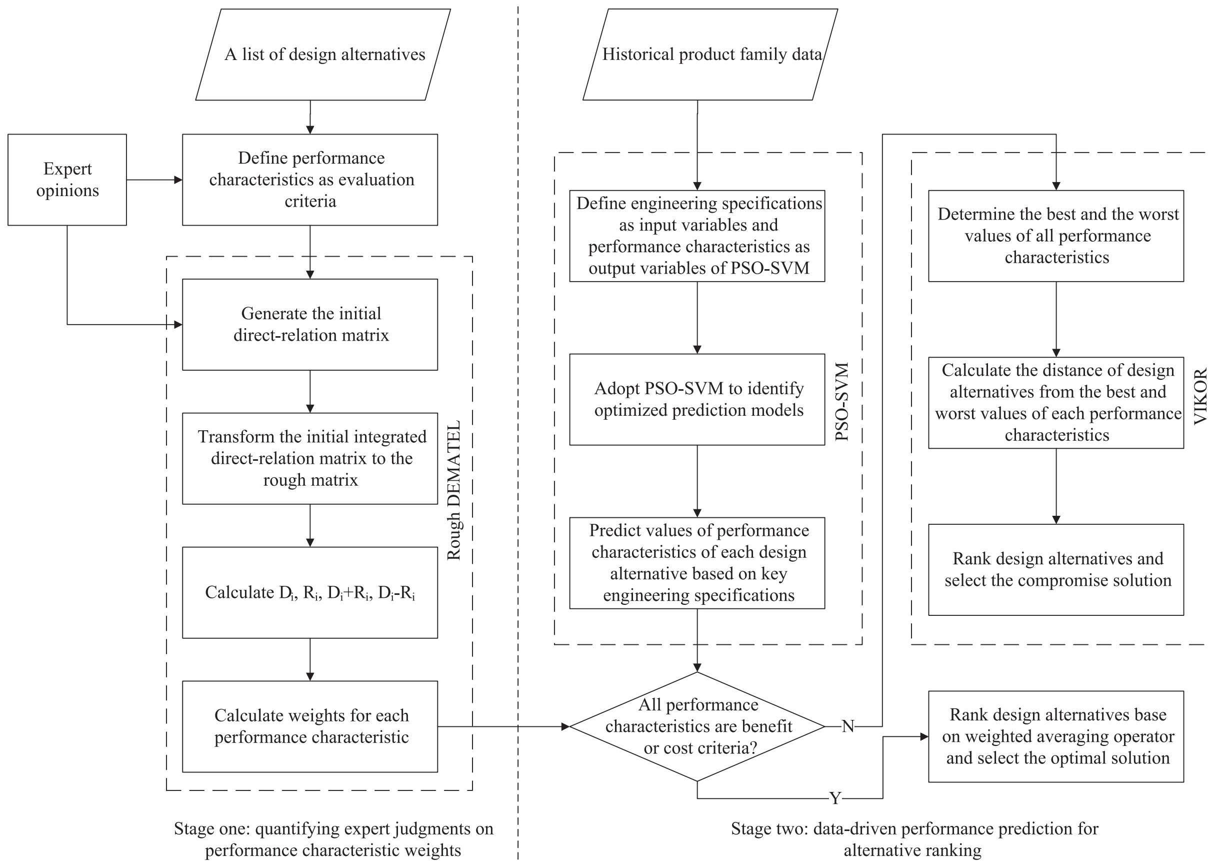

Fig. 1. Framework of the proposed method.

A large volume of literature is required to collect relevant information on each performance characteristic. A committee of experts, which can provide group knowledge for related issues, is also required. Based on the collected information and expert opinions, t different performance characteristics are selected as evaluation criteria.

(2) Generate the initial direct-relation matrix

The expert interview method is used to gain each experts' assessments about the degree of direct-relation influence between each performance characteristic. To manage the vagueness of expert's judgment information, the linguistic variable "influence" is classified using different linguistic terms which are expressed with corresponding scores. The initial direct-relation matrix of the eth expert is described below:

$$A_e = \begin{bmatrix} 0 & \cdots & a^e_{1j} & \cdots & a^e_{1t} \\ \vdots & & \vdots & & \vdots \\ a^e_{i1} & \cdots & a^e_{ij} & \cdots & a^e_{it} \\ \vdots & & \vdots & & \vdots \\ a^e_{t1} & \cdots & a^e_{tj} & \cdots & 0 \end{bmatrix}_{t\times t}$$

where $a^e_{ij}(1 \leqslant i \leqslant t; 1 \leqslant j \leqslant t, 1 \leqslant e \leqslant s)$ indicates linguistic score that reflects direct-relation influence degree of performance characteristic i on performance characteristic j given by eth expert.

Then all experts' initial direct-relation matrixes are integrated. The initial integrated direct-relation matrix $\tilde{A}$ is built as:

$$\tilde{A} = \begin{bmatrix} 0 & \cdots & \tilde{a}_{1j} & \cdots & \tilde{a}_{1t} \\ \vdots & & \vdots & & \vdots \\ \tilde{a}_{i1} & \cdots & \tilde{a}_{ij} & \cdots & \tilde{a}_{it} \\ \vdots & & \vdots & & \vdots \\ \tilde{a}_{t1} & \cdots & \tilde{a}_{tj} & \cdots & 0 \end{bmatrix}_{t\times t}$$

where $\tilde{a}_{ij} = \{a^1_{ij}, a^2_{ij}, \ldots, a^s_{ij}\}$, $\tilde{a}_{ij}$ is the sequence of direct-relation influence degree of performance characteristic i on performance characteristic j.

(3) Construct the rough direct-relation matrix

Based on the definition of rough number [4,64], a^e_{ij} in $\widetilde{A}$ can be converted into rough number $RN(a^e_{ij})$ as follow.

$$RN(a^e_{ij}) = \lceil a^{eL}_{ij}, a^{eU}_{ij} \rfloor$$

where a^{eL}_{ij} indicates the lower limit, and a^{eU}_{ij} represents the upper limit.

In this way, the rough sequence $RN(\tilde{a}_{ij})$ is represented as:

$$RN(\tilde{a}_{ij}) = \left\{\lceil a^{1L}_{ij}, a^{1U}_{ij} \rfloor, \lceil a^{2L}_{ij}, a^{2U}_{ij} \rfloor, \ldots, \lceil a^{sL}_{ij}, a^{sU}_{ij} \rfloor\right\}$$

Based on rough arithmetic [4], an average rough number $RN(a_{ij})$, which represents aggregation of the experts' assessments, can be calculated as follows:

$$RN(a_{ij}) = \lceil a^L_{ij}, a^U_{ij} \rfloor \quad \text{where} \quad a^L_{ij} = \frac{a^{1L}_{ij} + a^{2L}_{ij} + \cdots + a^{sL}_{ij}}{s}, a^U_{ij} = \frac{a^{1U}_{ij} + a^{2U}_{ij} + \cdots + a^{sU}_{ij}}{s} \tag{2}$$

Accordingly, the rough direct-relation matrix $\hat{A}$ is constructed as

$$\hat{A}=\begin{bmatrix} 0 & \cdots & \lceil a_{1j}^{L},a_{1j}^{U}\rfloor & \cdots & \lceil a_{1t}^{L},a_{1t}^{U}\rfloor \\ \vdots & & \vdots & & \vdots \\ \lceil a_{i1}^{L},a_{i1}^{U}\rfloor & \cdots & \lceil a_{ij}^{L},a_{ij}^{U}\rfloor & \cdots & \lceil a_{it}^{L},a_{it}^{U}\rfloor \\ \vdots & & \vdots & & \vdots \\ \lceil a_{t1}^{L},a_{t1}^{U}\rfloor & \cdots & \lceil a_{tj}^{L},a_{tj}^{U}\rfloor & \cdots & 0 \end{bmatrix}_{t\times t}$$

(4) Normalize the rough direct-relation matrix

According to the rough direct-relation matrix $\hat{A}$, the normalized rough direct-relation matrix $\hat{Z}=[\hat{z}_{ij}]_{t\times t}$ can be found as follows:

$$\hat{Z}=\frac{1}{\max\limits_{1\leqslant i\leqslant t}\sum_{j=1}^{t}a_{ij}^{U}}\hat{A} \tag{3}$$

(5) Determine the rough total-relation matrix

The rough total-relation matrix $\hat{T}$ can be derived from normalized rough direct-relation matrix, obtained as follows:

$$\begin{aligned}\hat{T}&=\hat{Z}+\hat{Z}^{2}+\cdots+\hat{Z}^{h}=\hat{Z}(I-\hat{Z}^{h})(I-\hat{Z})^{-1},\\ &=\hat{Z}(I-\hat{Z})^{-1},\quad \text{when}\quad \lim_{h\to\infty}\hat{Z}^{h}=[0]_{t\times t}\end{aligned} \tag{4}$$

I indicates identity matrix.

Specific calculation of the rough total-relation matrix $\hat{T}=[\hat{t}_{ij}]_{t\times t}$ is similar to the process of obtaining the fuzzy total-relation matrix [10]. Matrix $\hat{T}$ represents the total-relations between each pair of performance characteristics.

(6) Calculate the sum of rows and columns of the rough total-relation matrix

The sum of each row and each column of the matrix $\hat{T}$ are separately denoted as $\hat{D}_i$ and $\hat{R}_j$ using Eqs. (5) and (6).

$$\hat{D}_i=\sum_{1\leqslant j\leqslant t}\hat{t}_{ij} \tag{5}$$

$$\hat{R}_j=\sum_{1\leqslant i\leqslant t}\hat{t}_{ij} \tag{6}$$

$\hat{D}_i$ indicates all direct and indirect influence of performance characteristic i on all other performance characteristics. $\hat{R}_j$ denotes all direct and indirect influence that performance characteristic j has received from the other performance characteristics.

$\hat{D}_i$ and $\hat{R}_j$ can be transformed into crisp values using Eqs. (7) and (8).

$$D_i=\frac{\left(D_i^{L}+D_i^{U}\right)}{2},\quad \text{where}\quad \lceil\hat{D}_i=D_i^{L},D_i^{U}\rfloor \tag{7}$$

$$R_j=\frac{\left(R_j^{L}+R_j^{U}\right)}{2},\quad \text{where}\quad \lceil\hat{R}_j=R_j^{L},R_j^{U}\rfloor \tag{8}$$

When $i=j$, D_i+R_i represents the degree of performance characteristic i being influenced and influencing other performance characteristics. It reflects the extent of importance of performance characteristic i. In addition, D_i-R_i denotes the net effect that performance characteristic i has on the other performance characteristics. Particularly, if the value of D_i-R_i is positive, the performance characteristic i is regarded as having a causal role in affecting other performance characteristics, and if the value of D_i-R_i is negative, the performance characteristic i is considered as having a result role, influenced by the other performance characteristics.

(7) Calculate the weights of the performance characteristics

After rough numbers of importance degree and net effect degree are converted to crisp values, the weight of each performance characteristic can be computed by Eq. (9).

$$\begin{aligned}&w_i=\frac{M_i\times\left(1+N_i/\sum_{i=1}^{t}|N_i|\right)}{\sum_{i=1}^{t}\left[M_i\times\left(1+N_i/\sum_{i=1}^{t}|N_i|\right)\right]},\quad \text{where}\\ &M_i=D_i+R_i,\quad N_i=D_i-R_i\end{aligned} \tag{9}$$

3.3. Data-driven performance prediction for alternative ranking

After identifying the weight of each performance characteristic, the evaluation values of performance characteristics for each design alternative should be obtained to rank all alternatives, and then select the optimal one. Due to the vagueness and incompleteness of information in the early design phases, normally, the evaluation values of performance characteristics for each design alternative are subjectively determined by the experts based on their domain knowledge and experience. These subjective and ambiguous evaluations can lead to poor quality of the selected design alternatives. Therefore, there is a need to improve the objectivity and accuracy in this evaluation process. The history design data of a product family provide a basis for discovering certain disciplinary knowledge about the complex nonlinear relationships between the engineering specifications and performance characteristics. It is conceivable that these relationships can be learned and modeled by data mining and knowledge discovery methods. The learned models can be applied to predict values of performance characteristics of each design alternative based on values of engineering specifications which are obtained after generating design alternatives. With the help of these models, decision makers are able to objectively and precisely rank and select design alternatives.

3.3.1. Construction of prediction model

Support vector machine (SVM) has been widely used as a powerful tool for solving nonlinear regression problems with limited size of training data [65]. Considering often-limited size of historical product family design data, we apply SVM to build nonlinear models for predicting values of performance characteristics. The predictive function $F(\boldsymbol{X})$ to be modeled relates the engineering specifications $\boldsymbol{X}=[x_1,x_2,\ldots,x_n]$ with the performance characteristic P. The training data for modeling is given as

$$\{[\boldsymbol{X}(1),P(1)],[\boldsymbol{X}(2),P(2)],\ldots,[\boldsymbol{X}(N),P(N)]\}$$

where N is the number of groups of training data. The core of SVM for modeling is to seek a smooth optimal function $F(\boldsymbol{X})$, which finds the predictive value $\hat{P}$ that satisfies at most ε deviation from the actual value P of the performance characteristic P for all training data. Experiences suggest that there exist complex nonlinear relationships between engineering specifications and performance characteristics. The idea of SVM solving this nonlinear problem is to map the input vectors $\boldsymbol{X}=[x_1,x_2,\ldots,x_n]$ into a high-dimensional space with the help of characteristic function $\Psi(\boldsymbol{X})$. In this paper, the pre-defined form of the predictive function of the performance characteristic could be formulated as follows:

$$F(\boldsymbol{X})=\langle\boldsymbol{w},\Psi(\boldsymbol{X})\rangle+b \tag{10}$$

where $\boldsymbol{w}$ denotes the weight vector and b represents the bias, they are model parameters to be trained. $\langle\cdot\rangle$is the dot product operation. Then, the function fitting problem is converted to the convex constrained optimization problem.

$$\min_{\boldsymbol{w},b,\xi,\xi^*} R(\boldsymbol{w},\xi_i,\xi_i^*) = \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{N}(\xi_i+\xi_i^*)$$
$$s.t.\begin{cases} P(i) - \langle \boldsymbol{w}, \Psi(\boldsymbol{X})\rangle - b \leqslant \varepsilon + \xi_i \\ \langle \boldsymbol{w}, \Psi(\boldsymbol{X})\rangle + b - P(i) \leqslant \varepsilon + \xi_i^* \end{cases} \tag{11}$$

where $\frac{1}{2}\|\boldsymbol{w}\|^2$ denotes the regularization term which measures the smoothness of the predictive function and therefore guarantees its generalization ability. C is the penalty factor prescribed parameter which measures the tradeoff between the training error and the generalization ability. ε is called the tube size, which controls the error threshold for the predictive function. ξ_i and ξ_i^* represent the upper and lower error at point $[\boldsymbol{X}(i), P(i)]$.

After that, the optimization problem is solved by the Lagrangian method. The corresponding Lagrangian function for dual training is expressed as

$$\max_{\alpha,\alpha^*} L(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\langle\Psi[\boldsymbol{X}(i)],\Psi[\boldsymbol{X}(j)]\rangle - \sum_{i=1}^{N}[\varepsilon - P(i)]\alpha_i - \sum_{i=1}^{N}[\varepsilon + P(i)]\alpha_i^*$$
$$s.t.\begin{cases} \sum_{i=1}^{N}(\alpha_i-\alpha_i^*) = 0 \\ 0 \leqslant \alpha_i, \alpha_i^* \leqslant C \end{cases} \tag{12}$$

where α_i and α_i^* are the so-called Lagrangian multipliers.

By solving Eq. (12), $\boldsymbol{w}$ is obtained and shown as follow.

$$\boldsymbol{w} = \sum_{i=1}^{N}(\alpha_i-\alpha_i^*)\langle\Psi[\boldsymbol{X}(i)]\rangle \tag{13}$$

Based on Eqs.(10) and (13), the optimal predictive function is:

$$F(\boldsymbol{X}) = \sum_{i=1}^{N}(\alpha_i-\alpha_i^*)\langle\Psi[\boldsymbol{X}],\Psi[\boldsymbol{X}(i)]\rangle + b \tag{14}$$

$K[\boldsymbol{X},\boldsymbol{X}(i)]$, which equals $\langle\Psi[\boldsymbol{X}],\Psi[\boldsymbol{X}(i)]\rangle$, is called kernel function. There are several commonly used kernel functions, such as radial basis function (RBF), linear kernel function, polynomial basis function, and sigmoid function. RBF is adopted in this paper, because it can not only classify multi-dimensional data, but also has fewer parameters to adjust which avails to optimize parameters [56,65]. Additionally, SVM constructed by RBF has prominent nonlinear prediction performance [55]. RBF is shown as

$$K[\boldsymbol{X},\boldsymbol{X}(i)] = \exp\left(\frac{-\|\boldsymbol{X}-\boldsymbol{X}(i)\|^2}{2\sigma^2}\right) \tag{15}$$

where σ is the kernel width coefficient which controls the shape of this function.

The final form of SVM predictive model could be described as:

$$\hat{P} = F(\boldsymbol{X}) = \sum_{i=1}^{N}(\alpha_i-\alpha_i^*)\exp\left(\frac{-\|\boldsymbol{X}-\boldsymbol{X}(i)\|^2}{2\sigma^2}\right) + b \tag{16}$$

where $\hat{P}$ is the predicted value corresponding to the input $\boldsymbol{X}$.

According to Eqs. (11), (12) and (15), the prediction performance of SVM for construction of the predictive model depends on the hyper-parameters C (penalty factor), ε (tube size) and σ (kernel width coefficient). The hyper-parameters should be user-determined beforehand. Usually, they are identified either by repeated tests, which may result in repetitive tasks and difficulty in obtaining optimal values, or by experts, which often leads to bias and inaccuracy. As a powerful and popular searching algorithm, particle swarm optimization (PSO) is relatively easy to implement, understand and modify, and has fewer parameters to be adjusted and higher prediction accuracy when compared with other search algorithms, such as grid search(GS) and genetic algorithm (GA). Therefore, PSO is used to optimize hyper-parameters C, σ and ε to get a better optimization result.

In this section, by combining the advantages of PSO and SVM, a hybrid PSO-optimized SVM (PSO-SVM) model is adopted as an automated learning tool for discovering the complex relationship between engineering specifications and performance characteristics, and then constructing the optimized prediction model. The construction process of optimized prediction model based on PSO-SVM is shown in Fig. 2, which is described below [55,65].

(1) Define and initialize particles. The particles of PSO are defined by its position and velocity as follows:

$$\boldsymbol{L}_j = [l_j^C, l_j^\varepsilon, l_j^\sigma] \quad j = 1,2,\ldots,M \tag{17}$$

$$\boldsymbol{v}_j = \left[v_j^C, v_j^\varepsilon, v_j^\sigma\right] \quad j = 1,2,\ldots,M \tag{18}$$

where M is number of particles. The particles are initialized according to the uniformly random distributed principle. Then, the particles are iteratively updated. Each particle in the tth iteration is defined by the position $\boldsymbol{L}_j(t)$ in the search space, the personal best position $\boldsymbol{L}_{jbest}(t)$ during iteration $1 \sim t$, the velocity $\boldsymbol{v}_j(t)$ and the global best position $\boldsymbol{L}_{gbest}(t)$ for the whole particle swarm.

(2) Then, the iteratively updated functions of velocity $\boldsymbol{v}_j$ and position $\boldsymbol{L}_j$ for each particle are defined as:

$$\boldsymbol{v}_j(t+1) = \omega\boldsymbol{v}_j(t) + c_1r_1\left[\boldsymbol{L}_j(t) - \boldsymbol{L}_{jbest}(t)\right] + c_2r_2\left[\boldsymbol{L}_j(t) - \boldsymbol{L}_{gbest}(t)\right] \tag{19}$$

$$\boldsymbol{L}_j(t+1) = \boldsymbol{L}_j(t) + \boldsymbol{v}_j(t+1), \quad t = 1,2,\ldots,T \tag{20}$$

In the above formulas, T is the maximum evolutionary generation. ω is inertia factor which is used to balance the global exploration and local exploitation. c_1 and c_2 are personal and social learning factors, r_1 and r_2 are randomly generated numbers in a range $[0,1]$.

(3) After updating the velocities and positions, the new SVM predictive model $F_j(\boldsymbol{X})$ are trained by the updated particles $\boldsymbol{L}_j(t) = [l_{j,t}^C, l_{j,t}^\varepsilon, l_{j,t}^\sigma]$ which include hyper-parameters C, σ and ε. The corresponding predicted value $\hat{P}_{j,t}$ of the performance characteristic can be obtained through Eq. (16). Then, the fitness $R_j(t)$ is calculated by the normalized root mean square error (NRMSE), which is defined as:

$$R_j(t) = \sqrt{\frac{\sum_{i=1}^{N}\left[P(i) - \hat{P}_{j,t}(i)\right]^2}{\sum_{i=1}^{N}P^2(i)}} \tag{21}$$

where N is the number of groups of performance characteristic data, $R_j(t)$ represents the fitness of particle $\boldsymbol{L}_j(t)$, $P(i)$ is the actual value of the performance characteristic, $\hat{P}_{j,t}(i)$ stands for the predicted values of the performance characteristic, which is obtain from SVM model trained by particle $\boldsymbol{L}_j(t)$. The fitness $R_j(t)$ estimates the deviation of predicted value from the actual value with particle $\boldsymbol{L}_j(t)$.

(4) The fitness of $\boldsymbol{L}_{jbest}(t)$ and $\boldsymbol{L}_{gbest}(t)$, according to the minimal fitness in the swarm, are given as:

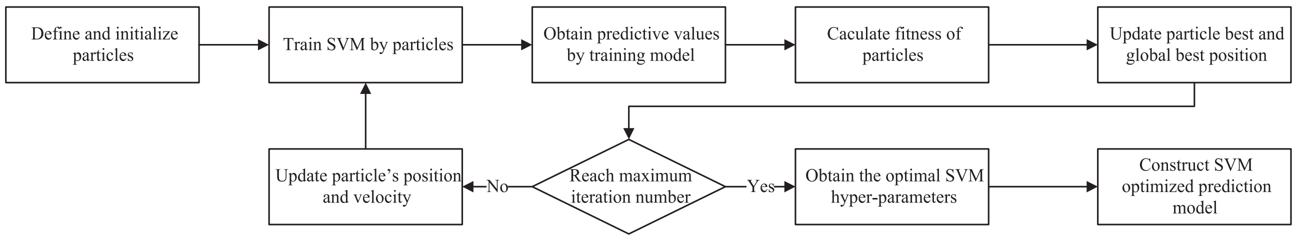

Fig. 2. the construction process of PSO-SVM.

$$R_{jbest}(t) = \min\{R_j(0), R_j(1), \ldots, R_j(t)\} \tag{22}$$

$$R_{gbest}(t) = \min\{R_{1best}(t), R_{2best}(t), \ldots, R_{Mbest}(t)\} \tag{23}$$

(5) Stop criterion is checked and if the maximal number of generations is reached, next step is proceeded; otherwise, back to Step 2. The optimum particle is expressed as

$$\boldsymbol{L}_{gbest} = \left[l_b^C, l_b^\varepsilon, l_b^\sigma\right] \tag{24}$$

(6) The optimized prediction model $F_{gbest}(\boldsymbol{X})$ is constructed based on l_b^C, l_b^ε and l_b^σ, which is shown as follow.

$$F_{gbest}(\boldsymbol{X}) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\exp\left(\frac{-\|\boldsymbol{X} - \boldsymbol{X}(i)\|^2}{2(l_b^\sigma)^2}\right) + b \tag{25}$$

3.3.2. Ranking of design alternatives based on VIKOR

After obtaining the weight of each performance characteristic and the performance characteristic values of each design alternative, we need to rank all alternatives, and then select the best one. In the previous work on design alternative ranking, TOPSIS and VIKOR are the most widely applied methods [3–6]. The VIKOR method was developed to overcome the shortcomings of the TOPSIS [59]. VIKOR introduces a ranking index based on the particular measure of "closeness" to the "ideal" alternative. Suppose there are m alternatives and t evaluation criteria, the multi-criteria measure for compromise ranking is developed from the L_p metric:

$$L_{p,i} = \left\{\sum_{j=1}^{t}\left[w_j\left(f_j^+ - f_{ij}\right)/\left(f_j^+ - f_j^-\right)\right]^p\right\}^{1/p}, \quad 1 \leqslant p \leqslant \infty, \quad i = 1, 2, \ldots, m \tag{26}$$

where f_{ij} is the value of the jth criterion for the alternative A_i, w_j denotes the weight of jth criterion. f_j^+ and f_j^- represent the best and worst values for jth criterion, separately. The VIKOR method deploys $L_{1,i}$ (as S_i) and $L_{\infty,i}$ (as R_i) to formulate the ranking measure. The compromise ranking algorithm of VIKOR is briefly reviewed as follows [59]:

Step 1: Construct a decision matrix.
Step 2: Determine the best f_j^+ and f_j^- values of all criteria. If the$j$th criterion represents a benefit: $f_j^+ = \max_i f_{ij}$, $f_j^- = \min_i f_{ij}$. If the$j$th criterion represents a cost: $f_j^+ = \min_i f_{ij}$, $f_j^- = \max_i f_{ij}$.
Step 3: Compute the values S_i and R_i, by the relations

$$S_i = \sum\nolimits_{j=1}^{t} w_j\left(f_j^+ - f_{ij}\right)/\left(f_j^+ - f_j^-\right) \tag{27}$$

$$R_i = \max_j\left[w_j\left(f_j^+ - f_{ij}\right)/\left(f_j^+ - f_j^-\right)\right] \tag{28}$$

where w_j denotes the weights of criteria.

Step 4: Compute the values Q_i as follows:

$$Q_i = \upsilon(S_i - S^-)/(S^+ - S^-) + (1-\upsilon)(R_i - R^-)/(R^+ - R^-) \tag{29}$$

where $S^+ = \max_i S_i$, $S^- = \min_i S_i$, $R^+ = \max_i R_i$, and $R^- = \min_i R_i$. υ is the weight of the strategy of "the majority of criteria" (or "the maximum group utility"), commonly $\upsilon = 0.5$.

Step 5: Rank the alternatives, sorting by the values S_i, R_i and Q_i, in ascending order.
Step 6: Propose as a compromise solution the alternative $A^{(1)}$ which is ranked the best by the measure Q (minimum) if the following two conditions are satisfied.

C1. "Acceptable advantage"

$$Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \geqslant \frac{1}{m-1} \tag{30}$$

where $A^{(2)}$ is the alternative with second position in the ranking list by Q_i, and m is the total number of alternatives.

C2. "Acceptable stability in decision making"

Alternative $A^{(1)}$ must also be the best ranked by S_i and/or R_i. This compromise solution is stable within a decision-making process, which could be "voting by majority rule" (when $\upsilon > 0.5$ is needed), or "by consensus" ($\upsilon \approx 0.5$), or "with veto" ($\upsilon < 0.5$). Here, υ is the weight of the decision making strategy "the majority of criteria" (or "the maximum group utility").

When one of the conditions is not satisfied, then a series of compromise solutions is selected as follows:

(1) Alternatives $A^{(1)}$ and $A^{(2)}$ if only condition C2 is not satisfied, or
(2) Alternatives $A^{(1)}, A^{(2)}, \ldots, A^{(k)}$ if C1 is not satisfied. The maximum k in $A^{(k)}$ is determined by $Q(A^{(k)}) - Q(A^{(1)}) < \frac{1}{m-1}$ (the positions of these alternatives are "in closeness").

4. Case study

In this section, a set of design alternatives for a blow molding machine is used as an example to illustrate the application of the proposed approach in the real world. The blow molding machine has several complex function modules and each module is indicated by some engineering specifications. Through modifying and improving specific engineering specifications of function modules, new design alternatives are quickly generated to fulfill diverse market needs. The hierarchical structure of a blow molding machine design alternative is shown in Fig. 3. Company Z is located in southeastern China and majors in the field of designing and manufacturing all types of blow molding equipment, suitable for manufacturing hollow plastic products. To realize new market requirements, five blow molding machine alternatives have been

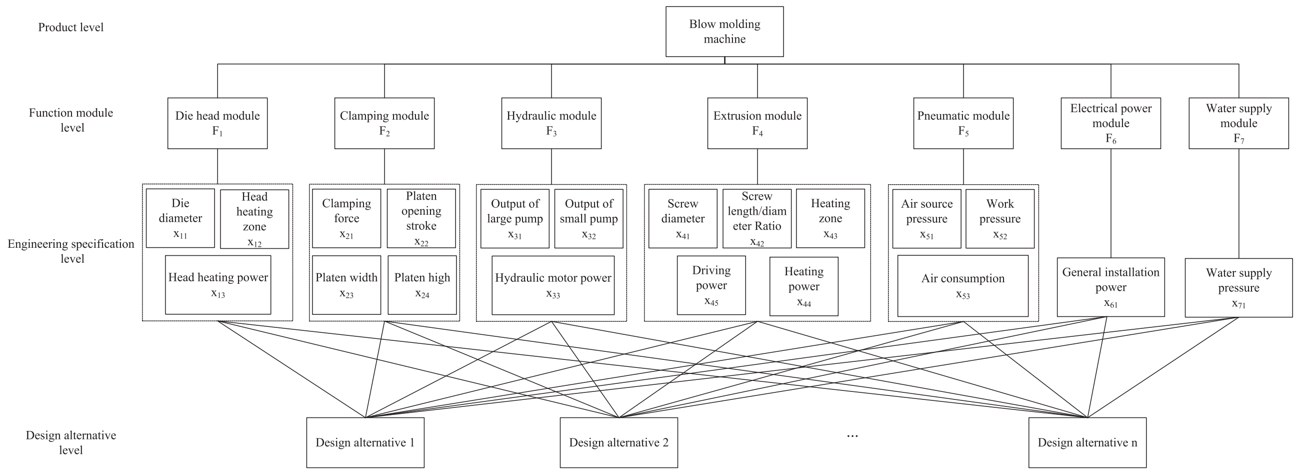

Fig. 3. The hierarchical structure of a blow molding machine design alternative.

generated by designers, namely, A_1, A_2, A_3, A_4 and A_5. The goal of the evaluation is to identify the best alternative. The feature of each alternative is outlined in Table 1.

Kano questionnaires [66,67] were designed and distributed to invited customers to examine their perceptions of product features for characterizing an ideal blow molding machine. To enhance the reliability and validity of the surveyed questionnaires, the invited customers with at least three years of user experience, were selected to carry out marketing surveys. The functional question in Kano questionnaires is like "If the blow molding machine can service for 10 years, how would you feel?" The dysfunctional question is like "If the blow molding machine can service for 10 years, how would you feel?". In this research, 42 effective samples are collected. The customer survey reveals that, customers show interest in reliable, productive and cost effective performance of a blow molding machine. Therefore, in order to satisfy customers basic requirements, a team of experts in technology management and product development at earlier design stages has identified four core performance characteristics of the blow molding machine which are namely, plasticizing capacity (P_1), output per hour (P_2), average energy consumption (P_3) and maximum volume of a product (P_4). Among them, P_1, P_2 and P_4 are the benefit criteria, and P_3 is the cost criterion. The evaluation process can be divided into three phases.

Phase (1): Obtain weights of performance characteristics based on rough DEMATEL.
Phase (2): Predict values of performance characteristics of each design alternative based on PSO-SVM.
Phase (3): Rank and select the design alternatives based on VIKOR.

4.1. Obtain weights of performance characteristics

DEMATEL is used by experts to determine the relationships of these performance characteristics. Rough number is used to express the experts' evaluation information, reducing the ambiguity and uncertainty during the decision-making process. An expert interview method is applied to fifteen experienced experts to obtain the direct-relation influence relationships among the four performance characteristics P_1, P_2, P_3 and P_4. $E = \{e_1, e_2, \ldots, e_{15}\}$ represents the set of experienced experts. To cope with the vagueness of expert judgments, the linguistic variable "influence" is classified with five linguistic terms as {Very high, High, Low, Very low, No} that are accordingly expressed with scores 4, 3, 2, 1 and 0 [21].

Data collected from the experts was analyzed with the rough DEMATEL method. The major steps were conducted as follows.

Step 1. Generate the initial direct-relation matrix

The judgments of fifteen experts on initial direct-relation influence relationships among performance characteristics are collected. Then the initial integrated direct-relation matrix $\tilde{A}$ is generated by combining the fifteen initial direct-relation matrixes.

$$\tilde{A} = \begin{bmatrix} \overbrace{0,0,\ldots,0}^{15} & 4,4,\ldots,1 & 3,0,\ldots,4 & 4,2,\ldots,2 \\ 4,1,\ldots,2 & 0,0,\ldots,0 & 3,4,\ldots,0 & 0,4,\ldots,3 \\ 3,4,\ldots,2 & 2,4,\ldots,0 & 0,0,\ldots,0 & 1,4,\ldots,3 \\ 3,2,\ldots,4 & 1,1,\ldots,,1 & 1,0,\ldots,0 & 0,0,\ldots 0 \end{bmatrix}$$

Step 2. Construct the rough direct-relation matrix

Based on the definition of rough number [4,64], crisp values in the initial integrated direct-relation matrix $\tilde{A}$ can be converted into corresponding rough numbers.

Take $\tilde{a}_{12} = \{4, 4,\ 4,\ 1,\ 4,\ 4,\ 0,\ 4,\ 3,\ 3,\ 2,\ 4,\ 3,\ 1,\ 1\}$ as an example.

$$\underline{Lim}(4) = \frac{1}{15}(4+4+4+1+4+4+0+4+3+3+2+4 \\ +3+1+1) = 2.8, \overline{Lim}(4) = 4$$

$$\underline{Lim}(3) = \frac{1}{8}(1+0+3+3+2+3+1+1) = 1.75$$

$$\overline{Lim}(3) = \frac{1}{10}(4+4+4+4+4+4+3+3+4+3) = 3.7$$

$$\underline{Lim}(2) = \frac{1}{5}(1+0+2+1+1) = 1$$

$$\overline{Lim}(2) = \frac{1}{11}(4+4+4+4+4+4+3+3+2+4+3) = 3.545$$

$$\underline{Lim}(1) = \frac{1}{4}(1+0+1+1) = 0.75$$

$$\overline{Lim}(1) = \frac{1}{14}(4+4+4+1+4+4+4+3+3+2 \\ +4+3+1+1) = 3$$

$$\underline{Lim}(0) = 0, \overline{Lim}(0) = \frac{1}{15}(4+4+4+1+4+4+0+4+3 \\ +3+2+4+3+1+1) = 2.8$$

Thus, a_{12}^e can be expressed in rough number:

$$RN(a_{12}^1) = RN(a_{12}^2) = RN(a_{12}^3) = RN(a_{12}^5) = RN(a_{12}^6)$$
$$= RN(a_{12}^8) = RN(a_{12}^{12}) = RN(4) = \lceil 2.8, 4 \rfloor$$
$$RN(a_{12}^4) = RN(a_{12}^{14}) = RN(a_{12}^{15}) = RN(1) = \lceil 0.75, 3 \rfloor$$
$$RN(a_{12}^7) = RN(0) = \lceil 0, 2.8 \rfloor$$
$$RN(a_{12}^9) = RN(a_{12}^{10}) = RN(a_{12}^{13}) = RN(3) = \lceil 1.75, 3.7 \rfloor$$
$$RN(a_{12}^{11}) = RN(2) = \lceil 1, 3.545 \rfloor$$

Based on Eq. (2), the rough sequence $RN(\tilde{a}_{12})$ in $\tilde{A}$ is converted into an average rough number $RN(a_{12}) = \lceil 10.873, 30.63 \rfloor$. The other elements in $\tilde{A}$ can be converted in the same way. Then, the rough direct-relation matrix, $\hat{A}$ is shown as follow.

$$\hat{A} = \begin{bmatrix} \lceil 0,0 \rfloor & \lceil 1.873, 3.63 \rfloor & \lceil 1.572, 3.557 \rfloor & \lceil 1.827, 3.539 \rfloor \\ \lceil 1.648, 3.351 \rfloor & \lceil 0,0 \rfloor & \lceil 1.457, 3.403 \rfloor & \lceil 0.899, 2.909 \rfloor \\ \lceil 1.224, 3.342 \rfloor & \lceil 1.048, 3.164 \rfloor & \lceil 0,0 \rfloor & \lceil 1.206, 3.05 \rfloor \\ \lceil 0.893, 2.525 \rfloor & \lceil 0.483, 2.02 \rfloor & \lceil 0.89, 2.742 \rfloor & \lceil 0,0 \rfloor \end{bmatrix}$$

Step 3. Normalize the rough direct-relation matrix

The rough direct-relation matrix $\hat{A}$ can be normalized by Eq. (3). The normalized rough direct-relation matrix $\hat{Z}$ is shown as follow.

$$\hat{Z} = \begin{bmatrix} \lceil 0,0 \rfloor & \lceil 0.175, 0.338 \rfloor & \lceil 0.147, 0.332 \rfloor & \lceil 0.17, 0.33 \rfloor \\ \lceil 0.154, 0.312 \rfloor & \lceil 0,0 \rfloor & \lceil 0.136, 0.317 \rfloor & \lceil 0.084, 0.271 \rfloor \\ \lceil 0.114, 0.312 \rfloor & \lceil 0.098, 0.295 \rfloor & \lceil 0,0 \rfloor & \lceil 0.112, 0.284 \rfloor \\ \lceil 0.083, 0.235 \rfloor & \lceil 0.045, 0.188 \rfloor & \lceil 0.083, 0.256 \rfloor & \lceil 0,0 \rfloor \end{bmatrix}$$

Step 4. Determine the rough total-relation matrix

The rough total-relation matrix $\hat{T}$ can be derived from the normalized rough direct-relation matrix $\hat{Z}$ by Eq. (4).

$$\hat{T} = \begin{bmatrix} \lceil 0.076, 1.615 \rfloor & \lceil 0.218, 1.812 \rfloor & \lceil 0.206, 1.929 \rfloor & \lceil 0.225, 1.903 \rfloor \\ \lceil 0.196, 1.738 \rfloor & \lceil 0.059, 1.449 \rfloor & \lceil 0.184, 1.801 \rfloor & \lceil 0.143, 1.75 \rfloor \\ \lceil 0.154, 1.721 \rfloor & \lceil 0.137, 1.66 \rfloor & \lceil 0.054, 1.543 \rfloor & \lceil 0.156, 1.741 \rfloor \\ \lceil 0.111, 1.383 \rfloor & \lceil 0.077, 1.312 \rfloor & \lceil 0.113, 1.443 \rfloor & \lceil 0.038, 1.223 \rfloor \end{bmatrix}$$

Step 5. Calculate $D_i + R_i$, $D_i - R_i$ and w_i of each performance characteristic

The sum of every row and every column of the matrix $\hat{T}$ can be computed and then transformed into a crisp value by Eqs. (5)–(8).

Table 1
The feature of each design alternative.

Alternative	Brief description of feature
A_1	A_1 is an economical standard type which has double stations, 5.5 kW head heating power, 25 kN clamping force, 5.5 kW hydraulic motor power, 0.3 m^3/min air consumption and 0.3 MPa water supply pressure
A_2	A_2 is a high speed standard type which has double stations, 6 kW head hearing power, 38 kN clamping force, 5.5 kW hydraulic motor power, 0.4 m^3/min air consumption and 0.3 MPa water supply pressure
A_3	A_3 is a full automatism type which has a single station, 7 kW head heating power, 60 kN clamping force, 5 kW hydraulic motor power, 0.4 m^3/min air consumption and 0.3 MPa water supply pressure
A_4	A_4 is a high speed standard type which has a single station, 7 kW head heating power, 78 kN clamping force, 6 kW hydraulic motor power, 0.4 m^3/min air consumption and 0.3 MPa water supply pressure
A_5.	A_5 is an economical standard type which has double stations, 7 kW head heating power, 30 kN clamping force, 5.5 kW hydraulic motor power, 0.3 m^3/min air consumption and 0.3 MPa water supply pressure

$D_i + R_i$ and $D_i - R_i$ of every performance characteristic can be calculated to reflect the extent of importance and the net effect of them, respectively. Finally, the weight of each performance characteristic can be computed using Eq. (9). The results of $D_i + R_i$, $D_i - R_i$ and w_i of each performance characteristic are shown in Table 2.

Based on the value of $D_i + R_i$, the extent of importance of performance characteristics are ranked as $P_1 > P_3 > P_2 > P_4$. Based on the value of $D_i - R_i$, the performance characteristics are divided into two groups. The cause group includes P_1 and P_2, and the result group is composed of P_3 and P_4. Taking the net effect into account, the $D_i - R_i$ value of each performance characteristic is added to modify the importance of them. The modified importance rank of performance characteristics is $P_1 > P_2 > P_3 > P_4$. It means that, in the view of experts, most attention should be given to plasticizing capacity when evaluating design alternatives.

4.2. Predict values of performance characteristic of design alternatives

As shown in Fig. 3, a blow molding machine has 20 engineering specifications in seven function modules. It is found that the four performance characteristics of a blow molding machine are influenced by these engineering specifications in different extent. We selected 25 historical products in the product family of company Z as the sample. A part of the original data are shown in Table 3.

Four predictive models $F_1(\boldsymbol{X})$, $F_2(\boldsymbol{X})$, $F_3(\boldsymbol{X})$ and $F_4(\boldsymbol{X})$ are constructed by PSO-SVM to predict values of plasticizing capacity (P_1), output per hour (P_2), average energy consumption (P_3) and maximum volume of a product (P_4), respectively. Building the prediction models based on the smaller number of engineering specifications can simplify the model for easier analysis. Thus, it is important to identify the key engineering specification sequences selected as the input variables of the predictive models. With the help of gray relation entropy analysis (GREA)[68,69], we can identify the correlation degrees of engineering specifications with each performance characteristic. According to the correlation degrees and opinions from design experts, for different performance characteristics, key engineering specification sequences are presented in Table 4.

The 25 groups of original data are divided into two data sets: training data set including 20 groups and testing data set including 5 groups. Before training, the original data are normalized to improve the generalization capability of PSO-SVM. For each predictive model, the performance characteristic is served as the output variable, and corresponding key engineering specifications in Table 4 are chosen as the input variables. Take plasticizing capability (P_1) as an example, the optimized predictive function $F_{gbest}^1(\boldsymbol{X})$ is modeled by PSO-SVM with training data set relates. The values of key engineering specifications $\boldsymbol{X} = [x_{31}, x_{41}, x_{42}, x_{43}, x_{45}, x_{51}, x_{52}]$ are the inputs of $F_{gbest}^1(\boldsymbol{X})$. The predictive value of $\hat{P}_1$ is the output of $F_{gbest}^1(\boldsymbol{X})$. The major steps of building the optimized predictive model $F_{gbest}^1(\boldsymbol{X})$ by PSO-SVM is shown below.

Firstly, the PSO is initialized as follows. The number of particles is set at 20. The maximum evolutionary generation is set at 200. The inertia factor is set at 1. The personal and social learning factors are respectively set at 1.5 and 1.7. The range of hyper-parameters $C = [0.1, 100]$, $\sigma = [0.001, 10]$ and $\varepsilon = [0.001, 10]$ are set by experience. Based on Eqs. (17) and (18), the particles which include hyper-parameters C, σ and ε are defined by its position and velocity, which are initialized according to the uniformly random distributed principle. Secondly, particles are updating based on Eqs. (19) and (20). The updated particles are implemented to train the predictive model $F_1(\boldsymbol{X})$. The fitness of each particle $R_j^1(t)$ can be implemented to train the predictive model $F_1(\boldsymbol{X})$. The fitness of each particle $R_j^1(t)$ can be obtained by Eq. (21) with 20 groups of

Table 2
The results of $D_i + R_i$, $D_i - R_i$ and w_i of each performance characteristic.

	$\hat{D}_i$	D_i	$\hat{R}_i$	R_i	$D_i + R_i$	$D_i - R_i$	w_i
P_1	⌜0.724, 7.259⌟	3.992	⌜0.537, 6.457⌟	3.497	7.489	0.495	0.344
P_2	⌜0.581, 6.738⌟	3.66	⌜0.491, 6.234⌟	3.362	7.022	0.297	0.292
P_3	⌜0.502, 6.665⌟	3.584	⌜0.557, 6.715⌟	3.636	7.22	−0.053	0.244
P_4	⌜0.339, 5.361⌟	2.85	⌜0.562, 6.617⌟	3.589	6.439	−0.739	0.12

Table 3
A part of original data.

Index	P_1 (kg/h)	P_2 (unit/h)	P_3 (kW/h)	P_4 (L)	x_{11} (mm)	x_{12}	x_{13} (kW)	x_{21} (kN)	x_{22} (mm)	x_{23} (mm)	x_{24} (mm)	x_{31} (ml/r.)
1	120	360	29	12	140	3	3.6	110	430	530	510	95
2	140	600	50	80	450	4	23	370	850	1000	1100	225
3	75	270	26	12	140	3	3.6	110	430	530	510	95
4	150	360	51	50	300	4	19	240	725	900	800	170
5	100	480	77	15	180	13	21	150	660	670	480	221

x_{32} (ml/r.)	x_{33} (kW)	x_{41} (mm)	x_{42}	x_{43}	x_{44} (kW)	x_{45} (kW)	x_{51} (MPa)	x_{52} (MPa)	x_{53} (M^3/min)	x_{61} (kW)	x_{71} (MPa)
45	11	90	24	4	18	37	0.8	0.6	0.2	64	0.25
38	37	100	24	4	20	45	1	0.8	0.4	119	0.25
45	11	70	24	3	13	22	0.8	0.6	0.2	50	0.25
36	30	90	25	4	24	45	0.7	0.6	0.4	120	0.3
85	39	75	30	4	21	45	0.7	0.6	2	135	0.3

Table 4
Key engineering specification sequence of each performance characteristic.

Performance characteristic	Key engineering specification sequence
Plasticizing capacity (P_1)	$x_{31}, x_{41}, x_{42}, x_{43}, x_{45}, x_{51}, x_{52}$
Output per hour (P_2)	$x_{22}, x_{23}, x_{41}, x_{43}, x_{45}, x_{61}$
Average energy consumption (P_3)	$x_{21}, x_{31}, x_{41}, x_{42}, x_{43}, x_{44}, x_{51}, x_{52}$
Maximum volume of a product (P_4)	$x_{11}, x_{23}, x_{24}, x_{42}, x_{43}, x_{44}$

training data. Thirdly, based on Eqs. (22) and (23), the global best fitness $R^1_{gbest}(t)$ in the swarm can be obtained. According to the global best fitness, the corresponding optimal hyper-parameters $\boldsymbol{L}^1_{gbest} = \left[l_b^{1C}, l_b^{1\varepsilon}, l_b^{1\sigma}\right]$ are acquired. Based on Eq. (25), the optimized predictive model $F^1_{gbest}(\boldsymbol{X})$ can be gained.

The optimized predictive model $F^2_{gbest}(\boldsymbol{X})$, $F^3_{gbest}(\boldsymbol{X})$ and $F^4_{gbest}(\boldsymbol{X})$ for performance characteristics P_2, P_3 and P_4 can be obtained in the same way. Table 5 presents the optimal hyper-parameters for different optimized predictive models.

The testing data sets are utilized to examine the accuracy of the optimized prediction model. For each group testing data, values of four key engineering specification sequences (in Table 4) are inputs of $F^1_{gbest}(\boldsymbol{X})$, $F^2_{gbest}(\boldsymbol{X})$, $F^3_{gbest}(\boldsymbol{X})$ and $F^4_{gbest}(\boldsymbol{X})$. The predictive values of four performance characteristics are outputs. Table 6 shows the actual and predictive of four performance characteristics using four optimized predictive models based on 5 groups testing data.

Mean absolute percentage error (MAPE) is used to evaluate the prediction accuracy, which is computed as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{P_t - \hat{P}_t}{P_t}\right| \tag{31}$$

where P_t and $\hat{P}_t$ are actual and predictive values, respectively, and N is the number of groups of testing data. The smaller the values of MAPE, the closer the predicted values are to the actual values.

Based on Eq. (31), the MAPE values of four optimized predictive models are 1.470%, 1.279%, 1.007% and 3.736%, separately. Therefore, the obtained four optimized predictive models are very good for predicting values of performance characteristics. The values of engineering specifications of five design alternatives are A_1, A_2, A_3, A_4, A_5 given after generating these alternatives. Based on above four models and given values of four key engineering specification sequences, the predicting values of performance characteristics of these alternatives can be obtained, which are shown in Table 7.

Table 5
The optimal hyper-parameters of optimized predictive models.

Optimized predictive model	Optimal hyper-parameters		
	C	σ	ε
$F^1_{gbest}(\boldsymbol{X})$ (plasticizing capacity)	5.988	0.100	0.010
$F^2_{gbest}(\boldsymbol{X})$ (output per hour)	84.415	0.161	0.021
$F^3_{gbest}(\boldsymbol{X})$ (average energy consumption)	2.684	0.904	0.010
$F^4_{gbest}(\boldsymbol{X})$ (maximum volume of a product)	3.598	0.450	0.053

4.3. Rank and select the alternatives

After obtaining the predictive values of performance characteristics of five design alternatives, VIKOR is implemented to determine the final rank. The decision matrix of the VIKOR method can be obtained according to Table 7. The best f_j^+ and the worst f_j^- values of all performance characteristics are listed in Table 8. The values S_i, R_i and Q_i are calculated using Eqs. (27)–(29), and the results and ranks in ascending order are shown in Table 9. According to Table 9, the final rank is obtained as follows: $A_1 < A_2 < A_3 < A_4 < A_5$. Considering the compromise conditions C1 and C2, the alternative A_5 satisfies both. Therefore, A_5 is determined as the best design alternative.

4.4. Comparison and discussion

In the previous section, an example was presented to show how the proposed method could be used to help engineers select best design alternative at the early stage of engineering design. In the following, to demonstrate some desirable features of our approach, we compare it with some traditional methods of the design alternative evaluation based on the data stated above.

Table 6
The actual and predictive values of performance characteristics using optimized predictive models.

Index	P_1 (kg/h)		P_2 (unit/h)		P_3 (kW/h)		P_4 (L)	
	PV	AV	PV	AV	PV	AV	PV	AV
1	90.951	90	362.576	360	28.208	28	12.21	12
2	46.045	45	1270.005	1280	20.284	20	1.976	1.8
3	181.268	180	532.459	540	64.777	65	122.423	120
4	118.651	120	607.229	600	36.141	36	61.46	60
5	61.286	60	1545.404	1560	20.265	21	5.135	5

Note: AV: actual value of each performance characteristic; PV: predictive value of each performance characteristic.

Table 7
Predictive values of performance characteristics and values of key engineering specifications of the five design alternatives.

Design alternative	Predictive value of performance characteristics				Values of key engineering specifications				
	P_1 (kg/h)	P_2 (unit/h)	P_3 (kW/h)	P_4 (L)	x_{11} (mm)	x_{21} (kN)	x_{22} (mm)	x_{23} (mm)	x_{24} (mm)
A_1	44.391	969.922	27.484	2.423	90	30	138	300	350
A_2	46.271	1007.745	22.932	2.961	140	25	100	260	245
A_3	65.391	1064.590	28.364	4.549	130	45	148	330	400
A_4	67.494	1292.459	31.185	4.794	140	45	148	330	400
A_5	63.783	1785.492	26.515	4.570	140	30	180	320	430

Values of key engineering specifications								
x_{31} (ml/r.)	x_{41} (mm)	x_{42}	x_{43}	x_{44} (kW)	x_{45} (kW)	x_{51} (MPa)	x_{52} (MPa)	x_{61} (kW)
53	60	24	3	11.5	15	0.6	0.6	36
42	65	25	3	7.2	11	0.7	0.6	32
53	60	24	3	11.5	15	0.6	0.6	40.2
53	70	24	3	12.6	22	0.6	0.6	49.3
42	75	25	3	11	15	0.7	0.6	35

Table 8
f_j^+ and f_j^- values of all performance characteristics.

	P_1	P_2	P_3	P_4
f_j^+	67.494	1785.492	22.932	4.794
f_j^-	44.391	969.922	31.185	2.423

Table 9
The values and ranks of S_i, R_i and Q_i.

Design alternative	S_i		R_i		Q_i	
	Value	Rank	Value	Rank	Value	Rank
A_1	0.891	5	0.344	5	1	5
A_2	0.687	4	0.316	4	0.8	4
A_3	0.462	3	0.258	3	0.521	3
A_4	0.421	2	0.244	2	0.463	2
A_5	0.173	1	0.106	1	0	1

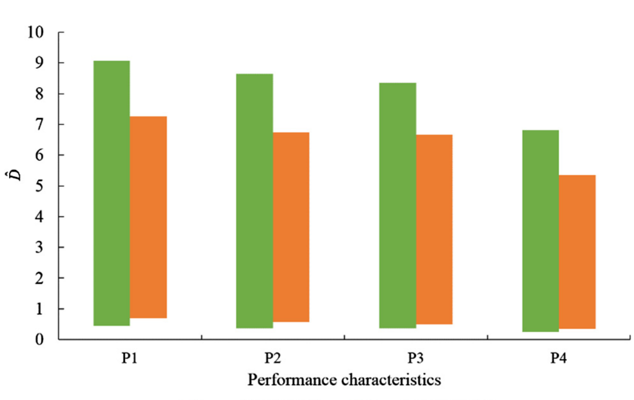

Fig. 4. Comparison of $\hat{D}$ by fuzzy DEMATEL and rough DEMATEL.

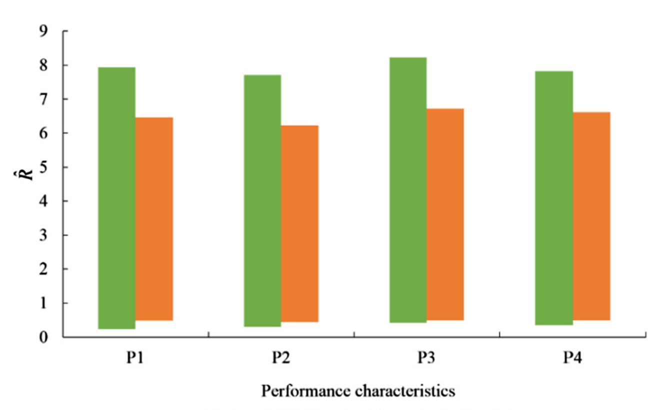

Fig. 5. Comparison of $\hat{R}$ by fuzzy DEMATEL and rough DEMATEL.

4.4.1. Effect of rough DEMATEL

The criterion weight has an impact on the final reliability of alternative ranking. To demonstrate the subjectivity manipulating mechanisms of criterion weights in rough DEMATEL, we compare it with fuzzy DEMATEL (using symmetrical triangular fuzzy number) [21]. Figs. 4 and 5 show the comparison of $\hat{D}$ and $\hat{R}$ by fuzzy DEMATEL and rough DEMATEL, respectively. These two DEMATEL methods have different interval boundaries meaning different levels of subjectivity and vagueness exist due to different manipulating mechanisms. The rough DEMATEL takes advantage of a flexible interval boundary in accordance with general distribution of experts' subjective judgments. However, the fuzzy DEMATEL adopts a fixed and static boundary according to preset membership function. The predefined membership function may lead to additional subjective information, which increases the deviations in the interval boundary as shown in Figs. 4 and 5. In short, the rough DEMATEL not only provides more flexibility, but also more objectively and effectively manipulates the experts' vagueness.

4.4.2. Competence of PSO-SVM

To confirm the prediction capability of PSO-SVM under the condition of a small amount of design data, a comparison of the predicting performance among PSO-SVM, GA-SVM, GS-SVM and ANN is presented in Fig. 6, where the four predictive methods are trained using the same training dataset and validated by the same testing dataset. Search algorithm based SVM has better prediction accuracy than ANN when given a small number of data. In addition, the PSO-SVM model can reach a smaller value for MAPE than GS-SVM and GA-SVM. The high stability of PSO-SVM can be concluded by comparing the results of different performance characteristics. In other words, it indicates that PSO-SVM has greater competence than GS-SVM, GA-SVM, and ANN in predicting the performance characteristics of design alternatives with historical product design data.

4.4.3. Insensitivity to experts' subjective opinions

Parameter v in VIKOR is the weight of the strategy of "the majority of criteria" (or "the maximum group utility"), which influences stability in decision making. To analyze the influence of the risks of experts' predilection on the final alternative rank, a set of sensitivity analyses is carried out. The Q values of each design alternative with varied v value is illustrated in Fig. 7. The best alternative is determined by the measure Q (minimum) and subjected to two conditions, which are shown in Section 3.3.2. When $0 \leqslant v \leqslant 1$, the final rank is obtained as $A_1 < A_2 < A_3 < A_4 < A_5$. Thus, all alternatives are independent of the risk propensity of experts. The results indicate that alternative A_5 has a maximum priority in all the situations, which reflect the influence of experts' propensity is weak in our approach.

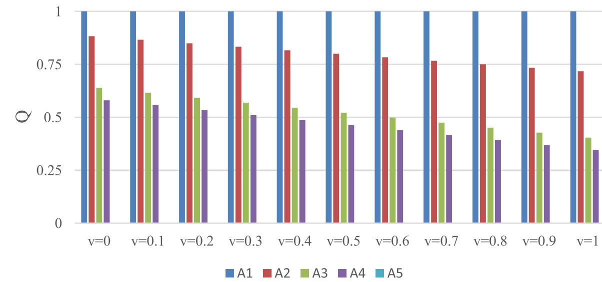

Fig. 7. The Q values of each design alternative with varied v value.

4.4.4. Features of quantitative alternative ranking

There have been many qualitative alternative ranking methods with the evaluation framework of VIKOR [4,6,10,25], but to our knowledge, there are few quantitative alternative ranking methods with VIKOR. To reveal the features of proposed quantitative design alternative ranking method PSO-SVM-VIKOR, we compare it with the qualitative design alternative ranking method, rough VIKOR [4,6]. In the expert-oriented method, namely rough VIKOR, fifteen experts are invited to evaluate the design alternatives using scale of 1, 3, 5, 7 and 9, which represent "very low," "low," "medium," "high," and "very high," respectively. Then, the scores for design alternatives can be given by a set of such values from experts' estimation. Based on the weights of performance characteristics calculated by rough DEMATEL, the Q value of each design alternative is determined by rough VIKOR. The Q values of design alternatives with PSO-SVM-VIKOR and rough VIKOR are shown in Fig. 8. According to this figure, when the value of v is different, the rank of design alternatives with PSO-SVM-VIKOR and rough VIKOR are always $A_1 < A_2 < A_3 < A_4 < A_5$ and $A_1 < A_3 < A_2 < A_4 < A_5$. The result of proposed method is almost the same as experts. Besides, two important features of the proposed quantitative method can be seen.

(1) *Efficiency*. There are differences in the ranks between the two kinds of evaluation approaches, but it is important to notice that A_5 is always the best alternative between quantitative and qualitative ranking method when taking different compromise strategies (which is reflected in different value of v). This indicates that the proposed quantitative method can validly and accurately evaluate design alternatives. As mentioned in Section 4.2, a blow molding machine has twenty engineering specifications in seven function modules. Even sophisticated experts need a long time to

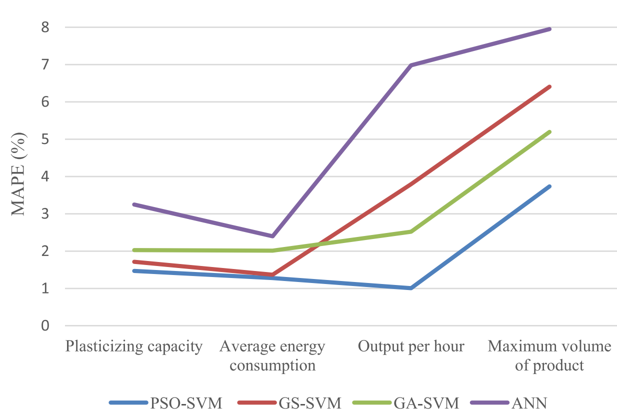

Fig. 6. MAPE value of predicting results for different performance characteristics using the PSO-SVM, GS-SVM, GA-SVM, ANN.

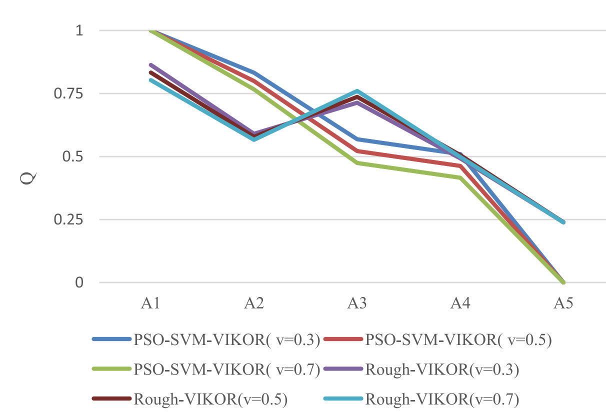

Fig. 8. The Q values from PSO-SVM-VIKOR and rough VIKOR.

infer the approximate values of four performance characteristics of each design alternative according to numerous engineering specifications. What's more, more time will be spent by them to compare five different alternatives in order to select the optimal one. With the help of the proposed quantitative method, alternative ranking may be done precisely and effectively in seconds and efforts from manual work can be largely reduced.

(2) *Objectivity.* According to rule C1 in Section 3.3.2, the alternative with second position in the ranking list by Q should be adequately deviated from the best one ($Q(A^{(2)}) - Q(A^{(1)}) \geqslant 0.25$). If not, it would lead to illusion in the final concept selection. As shown in Fig. 8, the Q value interval between the second alternative (A_4) and the best one (A_5) from rough VIKOR is closer to 0.25 than that from PSO-SVM-VIKOR. It can be inferred that when evaluating design alternative qualitatively, subjectivity and preference from experts would cause the confusion in differentiating two alternatives which possess similar capabilities of performance characteristics thus resulting the difficulty in selecting the best alternative. The quantitative ranking method, PSO-SVM-VIKOR which to a large extent avoids the human involvement has a clearer differentiation and can obtain more persuasive rank than the qualitative ranking method, rough VIKOR.

5. Conclusion

This paper presents a quantitative approach to evaluate design alternatives based on data-driven performance prediction. The proposed approach quantitatively analyzes expert judgments to determine weights of performance characteristics in the subjective and vague environment, and then ranks design alternatives based on predicting values of performance characteristics by using historical product data. The proposed approach is applied to the design alternative evaluation of a blow molding machine, and the results have demonstrated the validity and efficiency of the approach. With the help of the proposed approach, the objectivity and efficiency of the evaluation process can be enhanced by reducing vagueness and human involvement. The main features of the proposed approach are as follows.

The mutual relations among performance characteristics are explicitly and quantitatively taken into consideration when deciding on the criteria weights. The DEMATEL method is employed to analyze the impact of these relations identified by the experts and a rough number method is used to quantitatively deal with uncertainty and vagueness in the weight determination process. From discussion in Section 4.4, it can be seen that rough DEMATEL provides a more flexible and objective method of manipulating experts' judgment in weight determination than fuzzy DEMATEL.

Historical product design data provides a solid basis for enhanced prediction of performance values of design alternatives and for systematic ranking of alternatives

A PSO-SVM method is proposed to construct the prediction model based on historical product design data. VIKOR is applied to rank design alternatives based on predictive values of performance characteristic. These methods are integrated as an alternative ranking approach. The prediction accuracy of PSO-SVM is superior when compared with GS-SVM, GA-SVM, and ANN, and the overall PSO-SVM-VIKOR can be more time-saving and to larger extent reduce the bias and vagueness from experts when compared with the qualitative design alternative ranking method rough VIKOR, as indicated in Section 4.4.

The results of the case study together with the comparisons with other methods have indicated that the proposed quantitative design alternative approach is both effective and efficient. One limitation of the proposed method might be that the customer preference should be considered when determining the weights of performance characteristics in order to ensure the success of the product after launching to the market. In the future, other data mining methods, such as association rules analysis, will be implemented to discover the complex correlation and influence between customer needs and performance characteristics.

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