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Contents

Selection Of Port Enterprise Logistics Service Providers Based On The Combination Weighting-Grey Synthetic Decision-Making Method

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Abstract - **Selection of port enterprises logistics service providers is a complex multiple attribute decision-making problem. In order to improve the scientific nature of selection, a set of reasonable decision-making methods of logistics service providers selection are needed to establish. Accordingly, a combination weighting-grey synthetic decision-making method is proposed, which is used to solve the problem of providers selection. Firstly, this method combines the network analysis method with the entropy method to determine combined weights of evaluation indexes. Secondly, the improved center-point triangular whitenization weight function is introduced to cluster alternative plans and judge its corresponding grey classes, and then synthetic weighted decision-making vectors are used to solve grey synthetic decision-making coefficient vectors. Next, grey synthetic clustering decision-making coefficients are calculated to conduct a synthetic decision-making rank of alternative plans. Finally, an empirical study is conducted to verify the effectiveness of the proposed method by taking logistics service providers selection of a port enterprise.**

Keywords - **Combination weighting, grey synthetic decision-making, logistics service, providers selection**

I. INTRODUCTION

In the market environment, the reasonable choice of logistics service providers is one of the important problem that enterprises need to face. Due to the uncertainty of the evaluation process, it makes the problem appear the grey character, and causes it to become a complex multiple attribute decision-making problem [1]. At present, logistics service providers of port enterprises in our country are mainly small and medium sized enterprises. The overall strength and operation standardization degree of these companies are not high enough, they provide the quality of logistics service is also sometimes difficult to make port enterprises satisfaction. Therefore, the study of the selection strategy of port enterprises logistics service providers, has a certain practical significance to improve the operation efficiency and operation level of port enterprises.

To solve this problem, many scholars have done researches. Reference [2] introduced the compatibility of logistics service providers in the evaluation index system, through the network analysis method (ANP) for providers selection. Reference [3] introduced the grey clustering method in providers selection problem and established a decision-making model of grey clustering for providers evaluation. Reference [4] constructed the model of providers evaluation based on the extension AHP and the grey relational analysis method. Reference [5] constructed a double-layer planning model, respectively to the logistics cost and customer satisfaction as the optimization goal, and calculated the weight of each index by entropy method, finally using cloud adaptive genetic algorithm to solve the model. Reference [6] set up a double-layer planning model based on the logistics cost and service quality. In this foundation, the QFD model was reconstructed and the AHP was used to evaluate logistics service providers. Reference [7] used the ANP method to obtain corresponding weights based on the logistics strength, the cost price, the service quality and the cooperation risk of providers, then used the VIKOR to carry on the final sorting. Reference [8] combined the grey relational analysis and the TOPSIS method, then proposed a combination weighting GI-TOPSIS method was used to solve the logistics service providers selection problem. Reference [9] combined with the entropy method and the G1 method to evaluate providers. Reference [10] proposed using the rough set reduction theory to obtain the index system weight, and finally according to the TOPSIS method to calculate various logistics service providers to the close degree of the grey ideal solution to determine the appropriate provider. Reference [11] proposed a multiple objective decision-making model based on the grey clustering and the entropy weight method, which was used to select the best provider. Reference [12] combined the grey system theory with the ANP, and applied to evaluation and selection of logistics service providers. Reference [13] used the grey relational analysis method to choose providers, and through the change of weights to study the sensitivity of the change of the selection result. Reference [14] combined the entropy method with the principal component analysis method to solve weights, then the grey relational analysis method was used to select providers. In 2014, reference [15] improved the original center-point triangular whitenization weight function. In the new method, the class 1 was constructed to a whitenization weight function of lower measure, and the class s was constructed to a whitenization weight function of upper measure, through the improved center-point triangular whitenization weight function can effectively solve the extension problem of the range of each clustering index.

In summary, there are some shortcomings in selection of logistics service providers. For example, the index system cannot well reflect the interdependence relationship between indexes; the way of solving indexes weights too much rely on expert judgment and other subjective factors, the degree of attention to objective

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factors is not high enough; the way of handling the grey character of problem is not appropriate and so on. In this paper, to determine providers evaluation indexes weights not only considers the expert judgment and other subjective factors, but also considers the objective information of evaluation indexes data and the grey character. Accordingly, a combination weighting-grey synthetic decision-making method is proposed, which is used to help enterprises solve the problem of selecting logistics service providers, through empirical research, to verify the effectiveness of the decision-making method.

II. The evaluation index system of logistics service providers of port enterprises

A. Construction of the evaluation index system

Based on the existing research results, the evaluation index system of selecting logistics service providers of port enterprises is established, as shown in Table I.

B. Analysis of reliability and validity of the evaluation index system

According to the constructed evaluation index system above, the questionnaire survey is used to evaluate the importance of each evaluation index.

1) Reliability Analysis

Through the reliability analysis, the overall reliability coefficient of the questionnaire is 0.738. The internal consistency and reliability of the questionnaire are good.

2) Validity Analysis

According to the result of the analysis of validity, evaluation indexes are grouped into first level indexes of five groups, as shown in Table I.

III. The combination weighting-grey synthetic decision-making method

For a logistics service, there are m alternative plans on the market. There are n evaluation indexes for the evaluation of alternative plans. Evaluation data of alternative plans $i(i=1,2,...,m)$ about evaluation indexes $j(j=1,2,...,n)$ are $x_{ij}\,(i=1,2,...,m;\, j=1,2,...,n)$. This paper contains a total of s grey class. $w_j=(w_1,w_2,...,w_n)$ represents the combined weight of each evaluation index. In this paper, decision steps of the combination weighting-grey synthetic decision-making method are shown as follows.

A. Combination weighting

1) Determination of subjective weights based on the ANP method

Network structures of ANP are mainly composed of two parts: the control layer and the network layer. Elements can be divided into three relations, which are external influence relations, internal influence relations and mutual influence relations.

TABLE I
THE EVALUATION INDEX SYSTEM AND EVALUATION DATA OF LOGISTICS SERVICE PROVIDERS

Evaluation index		Alternative logistics service providers				
First level indexes	Second level indexes	G_1	G_2	G_3	G_4	G_5
Service quality A	Customer satisfaction rate A_1 (%)	83	80	87	89	84
	Order completion rate A_2 (%)	90	87	94	93	88
	On-time delivery rate A_3 (%)	85	86	87	88	89
	Product integrity rate A_4 (%)	90	94	91	93	94
	Problem handling rate A_5 (%)	92	88	94	89	91
Business ability B	Business diversity B_1 (Hundred mark)	81	77	88	85	84
	Logistics network B_2 (Hundred mark)	80	78	90	86	84
	Operation management ability B_3 (Hundred mark)	82	80	89	92	83
	Risk coping ability B_4 (Hundred mark)	67	63	72	69	77
Logistics cost C	Transportation cost C_1 (Vehicle 16M)	9300	8900	8800	8700	9600
	Storage cost C_2 (Yuan/(m^2*day))	2.8	3.3	3.6	3.8	3.4
	Circulation processing cost C_3 (Yuan/m^3)	17	20	14	12	16
	Handling and carrying cost C_4 (Yuan/t*1)	16	16	12	10	13
Enterprise soft power D	Market share D_1 (%)	5	5	6	4	3
	Enterprise qualification D_2 (Hundred mark)	87	82	92	93	90
	Enterprise reputation D_3 (Hundred mark)	78	82	80	79	84
	Professional talent ratio D_4 (%)	8	5	11	12	6
Cooperation E	Cooperation success rate E_1 (%)	74	77	86	88	83
	Informatization degree E_2 (Hundred mark)	82	72	80	68	81
	Communication level E_3 (Hundred mark)	75	85	83	83	69

By solving the limit matrix, the subjective weight s_j of each evaluation index is obtained.

2) Determination of objective weights based on the entropy method

Because there are some differences in the dimension of each evaluation index, therefore, before using the entropy method to solve objective weights, it is necessary to standardize evaluation data x_{ij}. When evaluation indexes are positive or reverse type, the standard formula (1) and (2) are used to convert evaluation data into non dimensional evaluation data r_{ij}.

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad j = 1,2,\cdots,n \tag{1}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad j = 1,2,\cdots,n \tag{2}$$

After standardized treatment, the objective weight o_j of each evaluation index is obtained through using the entropy method.

3) Calculation of combined weights

Combined weights of subjective weights and objective weights are calculated by the formula (3).

$$w_j = s_j \times o_j \Big/ \sum_{j=1}^{n} s_j \times o_j \quad j = 1,2,\cdots,n \tag{3}$$

B. Grey synthetic decision-making

1) Determination of turning points or center points of evaluation indexes grey classes

The value range of hypothesis evaluation indexes j are between [a_j, b_j]. According to overall evaluation requirements, evaluation indexes are divided into a total of s grey classes. Next, turning points λ_j^1 、 λ_j^s of grey classes 1 and grey classes s and center points λ_j^2 、 λ_j^3 … λ_j^{s-1} of grey classes $k(k \in \{2,3,...,s\text{-}1\})$ are determined respectively.

2) Construction of corresponding grey classes whitenization weight functions

Grey classes 1 are constructed to a corresponding whitenization weight function $f_j^1[-,-,\lambda_j^1,\lambda_j^2]$ of lower measure; grey classes s are constructed to a corresponding whitenization weight function $f_j^s[\lambda_j^{s-1},\lambda_j^s,-,-]$ of upper measure; for grey classes $k(k \in \{2,3,...,s\text{-}1\})$, they are needed to connect the point $(\lambda_k,1)$ and the center point $(\lambda_j^{k-1},0)$ of the grey class $k-1$ (or the turning point $(\lambda_j^1,0)$ of grey class 1) as well as the center point $(\lambda_j^{k+1},0)$ of the grey class $k+1$ (or the turning point

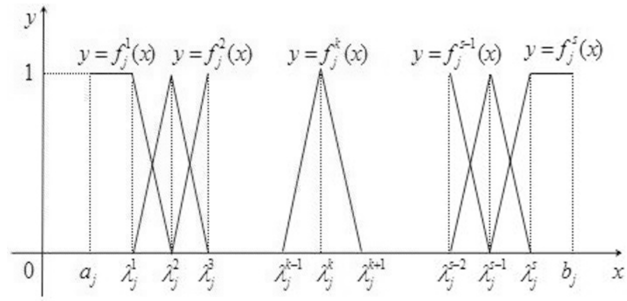

Fig.1. Schematic diagram of the improved center-point triangular whitenization weight function

$(\lambda_j^s,0)$ of grey class s). Thus, it can get triangular whitenization weight functions of evaluation indexes j for grey classes k. The function diagram shown in Figure 1.

3) The calculation of grey clustering coefficients

By the formula (4) we can calculate grey clustering coefficients σ_i^k of alternative plans $i(i = 1,2,...,m)$ for grey classes $k(k = 1,2,...,s)$.

$$\sigma_i^k = \sum_{j=1}^{n} f_j^k(x_{ij}) w_j \tag{4}$$

$f_j^k(x_{ij})$ represent whitenization weight functions of evaluation indexes j for grey classes k, w_j represent the combined weight of each evaluation index.

4) The judgment of alternative plans corresponding grey classes

Order $\delta_i^k = \dfrac{\sigma_i^k}{\sum_{k=1}^{s} \sigma_i^k}$, called δ_i^k as the normalized grey clustering coefficients of alternative plans i for grey classes k. Obviously, $\delta_i^k (k = 1,2,...,s)$ can meet the condition of $\sum_{i=1}^{s} \delta_i^k = 1$. $\delta_i = (\delta_i^1, \delta_i^2, ..., \delta_i^s)(i = 1,2,...,m)$ are called as the normalized grey clustering coefficient vectors of alternative plans i. According to the value of the $\max_{1 \le k \le s} \{\delta_i^k\} = \delta_i^{k^*}$, can judge alternative plans corresponding grey classes.

5) The calculation of synthetic weighted decision-making vectors

Assuming the existing a total of s grey classes, $\eta_k = (\eta_k^1, \eta_k^2, ..., \eta_k^s)(k = 1,2,...,s)$ are called synthetic weighted decision-making vector of grey classes k. The kth component of these vectors is assigned to the value s, and the kth component is took as the midpoint. When assigning a value to its left and right components, descending order, it indicates that the kth component is the largest contribution for alternative plans belonging grey classes k, so give it the greatest weight s. The calculation method is as follows:

$$\eta_k = \frac{(s-k+1, s-k+2, ..., s-1, s, s-1, ..., k)}{\frac{s(s+1)}{2} + [(k-1)s - k(k-1)]} \quad (5)$$

6) The calculation of grey synthetic decision-making coefficient vectors

By the formula (6) can calculate initial grey synthetic decision-making coefficients of alternative plans i for grey classes k, and $\psi_i' = (\psi_i^{1'}, \psi_i^{2'}, ..., \psi_i^{s'})(i=1,2,...,m)$ are called initial grey synthetic decision-making coefficient vectors of alternative plans i.

$$\psi_i^{k'} = \eta_k \delta_i^T \quad (6)$$

After the normalization process, we can get $\psi_i = (\psi_i^1, \psi_i^2, ..., \psi_i^s)(i=1,2,...,m)$ which are called grey synthetic decision-making coefficient vectors of alternative plans i.

7) The calculation of grey synthetic clustering decision-making coefficients

The weight vector of grey synthetic clustering decision-making coefficients is $\gamma = (1,2,...,s-1,s)^T$, by the formula (7) can calculate grey synthetic clustering decision-making coefficients π_i of alternative plans i.

$$\pi_i = \psi_i \cdot \gamma = \sum_{k=1}^{s} k \cdot \psi_i^k \, (i=1,2,...,m) \quad (7)$$

Because $0 \le \psi_i^k \le 1$, therefore, the maximum value of grey synthetic clustering decision-making coefficient $\pi_i = \psi_i \cdot \gamma (i=1,2,...,m)$ of alternative plans i is s, and the minimum value is 1. We can draw a conclusion: $1 \le \pi_i \le s$. At the same time, the decision-making coefficient matrix can be obtained as follows:

$$\pi_i = \begin{bmatrix} \pi_1 \\ \pi_2 \\ \cdots \\ \pi_m \end{bmatrix} = \begin{bmatrix} \psi_1^1 & \psi_1^2 & \cdots & \psi_1^s \\ \psi_2^1 & \psi_2^2 & \cdots & \psi_2^s \\ \cdots & \cdots & \cdots & \cdots \\ \psi_m^1 & \psi_m^2 & \cdots & \psi_m^s \end{bmatrix} \cdot (1,2,...,s-1,s)^T$$

8) The rank of the synthetic decision-making

By comparing the size of grey synthetic clustering decision-making coefficients of alternative plans i in the same grey classes k, we can conduct a synthetic decision-making rank.

IV. Empirical study

A port enterprise mainly produce various concrete block and concrete prefabricated components. These

TABLE II
EVALUATION INDEX COMBINATION WEIGHTS AND GREY CLASSES CLASSIFICATION OF LOGISTICS SERVICE PROVIDERS

Evaluation index			Turning points or center points of evaluation indexes grey classes					
First level indexes	Second level indexes	Combination weights	Lower limit	Poor	Medium	Good	Excellent	Upper limit
Service quality A	Customer satisfaction rate A_1 (%)	0.005	70	75	80	85	90	100
	Order completion rate A_2 (%)	0.020	70	80	85	90	95	100
	On-time delivery rate A_3 (%)	0.024	70	80	85	90	95	100
	Product integrity rate A_4 (%)	0.015	70	80	85	90	95	100
	Problem handling rate A_5 (%)	0.020	70	80	85	90	95	100
Business ability B	Business diversity B_1 (Hundred mark)	0.049	60	65	75	80	90	100
	Logistics network B_2 (Hundred mark)	0.087	60	70	75	85	90	100
	Operation management ability B_3 (Hundred mark)	0.174	60	65	75	85	90	100
	Risk coping ability B_4 (Hundred mark)	0.109	55	60	65	75	85	100
Logistics cost C	Transportation cost C_1 (Vehicle 16M)	0.034	10000	9800	9400	9000	8600	8000
	Storage cost C_2 (Yuan/(m^2*day))	0.025	8	4	3.5	3	2.5	2
	Circulation processing cost C_3 (Yuan/m^3)	0.011	30	25	19	15	11	10
	Handling and carrying cost C_4 (Yuan/t*1)	0.018	25	22	18	15	10	8
Enterprise soft power D	Market share D_1 (%)	0.036	0	1	3	5	7	10
	Enterprise qualification D_2 (Hundred mark)	0.170	70	75	80	85	90	100
	Enterprise reputation D_3 (Hundred mark)	0.059	60	65	75	85	90	100
	Professional talent ratio D_4 (%)	0.050	1	4	7	10	13	15
Cooperation E	Cooperation success rate E_1 (%)	0.018	60	70	75	85	90	100
	Informatization degree E_2 (Hundred mark)	0.053	60	65	70	75	80	100
	Communication level E_3 (Hundred mark)	0.023	55	60	70	80	85	100

TABLE III
GREY CLUSTERING COEFFICIENTS OF PROVIDERS

Grey clustering coefficients	Poor	Medium	Good	Excellent
G_1	0.004	0.346	0.506*	0.144
G_2	0.079	0.499*	0.378	0.044
G_3	0.005	0.097	0.290	0.608*
G_4	0.036	0.174	0.269	0.521*
G_5	0.036	0.197	0.480*	0.287

products are widely used in port and waterway engineering, buildings, roads and other buildings. Due to the limitation of the allocation of funds, the enterprise decide to choose logistics service providers to help them deal with the logistics business. Selection and evaluation of alternative providers are based on the combination weighting-grey synthetic decision-making method. Evaluation data of each alternative provider are shown in Table I.

A. Evaluation indexes combination weighting of port enterprise logistics service providers selection

By using the combination weighting method, combined weights of evaluation indexes of logistics service providers are obtained and results are shown in Table II.

B. Grey synthetic decision-making of port enterprise logistics service providers selection

1) Determination of turning points or center points of evaluation indexes grey classes

According to evaluation requirements, evaluation indexes of logistics service providers are divided into 4 grey classes: poor, medium, good and excellent, as shown in Table II.

2) Construction of corresponding grey classes whitenization weight functions

Taking the customer satisfaction rate as an example, the corresponding triangular whitenization weight function of lower measure $f_j^1[-,-,75,80]$ is constructed for the grey class 1; the corresponding triangular whitenization weight function of upper measure $f_j^4[85,90,-,-]$ is constructed for the grey class 4; the corresponding triangular whitenization weight functions $f_j^2[75,80,-,85]$ and $f_j^3[80,85,-,90]$ are constructed for the grey class 2 and the grey class 3.

3) The calculation of grey clustering coefficients

Grey clustering coefficients of each alternative provider are calculated and results are summarized as shown in Table III.

TABLE IV
PROVIDERS CORRESPONDING GREY CLASSES

G_1	G_2	G_3	G_4	G_5
Good	Medium	Excellent	Excellent	Good

TABLE V
GREY SYNTHETIC CLUSTERING DECISION-MAKING COEFFICIENTS OF PROVIDERS

	G_1	G_2	G_3	G_4	G_5
π_i	2.593	2.461	2.840	2.760	2.673

4) The judgment of alternative providers corresponding grey classes

By observing the maximum value of grey clustering coefficients of each alternative provider, it can be judged that providers belong to grey classes and results are shown in Table IV.

5) The calculation of synthetic weighted decision-making vectors

This paper involves four kinds of grey classes, which can be used to calculate synthetic weighted decision-making vectors of grey classes k:

$$\eta_1 = \frac{1}{10}(4,3,2,1); \eta_2 = \frac{1}{12}(3,4,3,2);$$

$$\eta_3 = \frac{1}{12}(2,3,4,3); \eta_4 = \frac{1}{10}(1,2,3,4)$$

6) The calculation of grey synthetic decision-making coefficient vectors

Calculate initial grey synthetic decision-making coefficient vectors of alternative providers i for grey classes k, after the normalization process, the grey synthetic decision-making coefficient vectors matrix can be obtained:

$$\psi_i = \begin{bmatrix} 0.209 & 0.252 & 0.276 & 0.263 \\ 0.246 & 0.271 & 0.259 & 0.224 \\ 0.153 & 0.211 & 0.279 & 0.357 \\ 0.174 & 0.223 & 0.272 & 0.331 \\ 0.192 & 0.236 & 0.279 & 0.293 \end{bmatrix}$$

7) The calculation of grey synthetic clustering decision-making coefficients

The grey synthetic clustering decision-making coefficient of each alternative provider is obtained, as shown in Table V.

8) The rank of the synthetic decision-making

According to results in Table IV and Table V: G_2 belongs to the medium grey class; G_1 and G_5 belongs to the good grey class, because of 2.673>2.593, so that G_5 is better than G_1; G_3 and G_4 belongs to the excellent grey class, because of 2.840>2.760, so that G_3 is better than G_4. The final ranking for alternative providers is: $G_3 > G_4 > G_5 > G_1 > G_2$. This result show that the provider G_3 has the largest grey synthetic clustering decision-making coefficient and the provider G_4 ranks second; Seeing from another angle, the provider G_2 is relatively poor. Therefore, the port enterprise should choose the provider G_3 as its partner, to help them deal with the logistics business.

V. CONCLUSION

Selection of logistics service providers is an important problem that enterprises must consider in supply chain management.Through the analysis of reliability and validity of the questionnaire, this paper determines the provider evaluation index system. Then, the network analysis method and the entropy method are combined to determine combined weights, the improved center-point triangular whitenization weight function is used to cluster alternative plans. Finally, grey synthetic clustering decision-making coefficients are calculated to make the synthetic decision-making rank of alternative plans. The validity of this method is proved through empirical research.

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Application of evaluation of aircraft material demand forecasting method and mining of association rules

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Abstract - **The support probability of aviation materials is a crucial part in the process of normal operation of airlines. But the higher support probability will inevitably lead to the increase of inventory cost of aviation materials, and restrict airlines to improve their efficiency. Hence it is of great significance for airlines reducing the material cost on the premise of normal operation to predict the material requirements accurately based on reasonable models. This paper summarizes a series of prediction models of aviation material requirements, and applies the grey comprehensive correlation degree to evaluate the models. On this basis, the method of association rules is used to discover the association relationships between the types of aviation materials and the prediction models.**

Keywords - **Association rule, aviation material prediction, grey comprehensive correlation degree, model recommendation**

I. INTRODUCTION

With the rapid development of China's economy, the aviation industry of China also has made great progress. However, with the rapid development, airlines are also facing with a series of questions. Especially, supply chain and security of aviation materials have been the focus of attention of each airline. The cost of aviation materials is an important part of aircraft operating costs of aviation transport enterprises, which ranks only second to the cost of purchase of aircraft and aviation fuel. Thus, to reduce aviation materials inventory cost of airlines effectively, it is crucial to predict the quantity demanded of aviation materials scientifically and reasonably.

At present, the study of methods of aviation materials demand forecasting has been paid highly attention by academia and application fields. Regattieri et al. applied the AW/M model to predict the fluctuant demands of spare parts of aviation materials [1]. Johnston et al. evaluated the optimal prediction parameters through analyzing the cycle length from 2 to 12, and built moving average model (MA(i)) to achieve prediction [2]. Aslam et al. put forward the prediction model based on exponentially weighted moving average [3]. Croston raised a method called Croston-CR, which overcame the shortage of exponential smoothing method, respectively evaluated the quantity demanded and the frequency of demand and prevented the shortage of inventory by adjusting the safety stock [4]. On the basis of Croston, Segerstedt computed the quantity of orders and order lead time [5]. Willemain et al. applied Croston's method to predict the intermittent demand for spare parts, which can bring tangible benefits for enterprises [6]. Godfrey carried out medicine research with linear regression model [7]. Isobe et al. applied linear regression model to research in astronomy [8]. Liu et al. used linear regression model to analyze near infrared spectrum [9]. And Figura applied it to predict underground water temperature [10]. Ramos et al. used ARIMA model to forecast consumer retail sales [11]. Li & Wang developed an automatic auto regressive integrated moving average modeling based data aggregation scheme in wireless sensor networks [12]. Chang et al. predicted the Internet users and the industry revenue of online games by using grey theory [13]. Ou applied GM(1,1) model to forecast the agricultural output [14]. Zhou et al. utilized GM(1,1) to predict the output of the fuel [15]. Yang & Shieh used SVR to predict consumers' affective responses [16].

The previous related research made outstanding contributions to improve the efficiency of demand forecasting. But in the practical application, the prediction methods suited to the different materials differ from one another. This paper put forward the prediction methods based on multi model and use grey comprehensive correlation degree to evaluate the predictive effect. And we mine the association pattern between material types and prediction models, so that the applicable prediction models can be given based on the association rules after airlines accumulating a certain amount of prediction record.

The paper is organized as follows: The second section mainly introduces the process of prediction and recommendation. In the section III, we make a case analysis. Finally, we present our conclusions in Section IV.

II. THE ANALYSIS AND RECOMMENDATION OF ALTERNATIVE PREDICTION MODELS

The statistical characteristics of different types of demand data of aviation materials are not the same. Because there are a great variety of aviation materials, it is difficult for each aviation material requirement to build and verify mathematical model respectively. To solve the above problems, eight prediction models are introduced to predict the aviation material requirements, which are Poisson distribution model, linear regression model, auto regression (AR) model, integrated autoregressive moving average (ARIMA) model, automatic arima model, holt-winters model, grey prediction model GM(1,1) and support vector machine regression (SVR) model. The TABLE I shows the description of the alternative prediction models.

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In this paper, the prediction and recommendation of material demand is divided into five steps:

(1) The preprocessing of data, including the outbound quantity, flight hours and flight frequency of aviation material;

(2) Multi model prediction. We apply eight kinds of prediction models to predict the demand of aviation material.

(3) Calculate the grey comprehensive correlation degree. Grey comprehensive correlation degree are used to evaluate the effect of prediction models.

(4) Mine the association rules. We apply apriori algorithm to mine the association pattern between material types and prediction models.

(5) Model recommendation. The optimal models are given based on the association rules mined by step (4) according to different aviation material.

III. RESULTS FOR CASE STUDY

In order to verify the multi prediction models and the model recommendation methods, this paper selected the monthly data of the material A of an airline company from January 2000 to July 2014, including the consumption quantity of the material A, the number of flight hours and the landing times. The detailed calculation and analysis results will be presented in the next part of this paper.

TABLE I
THE ALTERNATIVE PREDICTION MODELS

Name	Model description
Poisson distribution model	$$p_k(t)=\frac{(\lambda_t)^k}{k!}e^{-\lambda_t}, k\in Z^+, t>0 \quad (1)$$ $p_k(t)$ is the probability that the quantity demand of the aviation material is k within the time (0, t).
Linear regression model	Y_i is used to reflect the outbound quantity of aviation material, and X_i is the flight frequency or flight hours of aviation material. $$Y_i=a+bX_i+\varepsilon_i \quad (2)$$
Auto regression(AR) model	It is built according to the outbound quantity Y of aviation material. $$Y(t)=\varepsilon(t)+\sum_{i}^{p}\varphi_i Y(t-i) \quad (3)$$
ARIMA(p,d,q)	$$X(t)=\beta_0+\sum_{i=1}^{q}\beta_i X(t-i)-\varepsilon(t)-\sum_{j=1}^{p}\alpha_j\varepsilon(t-j) \quad (4)$$
Automatic arima model	There are tens of thousands of aviation materials in aviation enterprises. It is impossible for every time series data to arrange the staff to build model. Thus, it is necessary to introduce the automatic arima model, which can automatically identify the pattern of time series and estimate the parameters of models.
Holt-winters model	$$a_i=\alpha(y_i-c_{i-p})+(1-\alpha)(a_{i-1}+b_{i-1}) \quad (5)$$ $$b_i=\beta(a_i-a_{i-1})+(1-\beta)b_{i-1} \quad (6)$$ $$c_i=\gamma(y_i-a_{i-1}-b_{i-1})+(1-\gamma)c_{i-p} \quad (7)$$
Grey prediction model GM(1,1)	$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u \quad (8)$$ $x^{(1)}$ is the cumulative sequence in term of the historical outbound quantity of aviation material. t is the time. a,u are development grey number and Internal control grey number.
Support vector regression (SVR) model.	$$f(x)=w^t\phi(x)+b,\ w\in R^n, b\in R \quad (9)$$ The $f(x)$ reflects the historical outbound quantity of aviation material. x is flight hours or flight frequency. $\phi(x)$ is the nonlinear function.

A. The results of the prediction models

The paper selected the monthly data of the material A of an airline company from January 2000 to July 2014. Because the parameters of the model need a certain amount of data, the first 12 months of the data are only used to estimate of the model parameters, not to forecast the demand. Fig. 1 to Fig. 9 show the actual monthly outbound quantity of material A and eight kinds of prediction models from January 2001 to July 2014.

From the comparison of the actual demand with the forecasted results, among the eight models, the effect of grey prediction model GM(1,1) is the worst. Based on the analysis of the application of GM(1,1) in the grey forecasting model, it is generally believed that the necessary condition for obtaining high precision with GM(1, 1) model is that the equal time interval, the non negative and the monotonicity. Although the demand of A is satisfied with the equal time interval and the non negative, it is not satisfied with the monotone. So the prediction accuracy of the grey model GM(1,1) is poor. In contrast, the time series methods and the support vector machine regression model have better prediction effect.

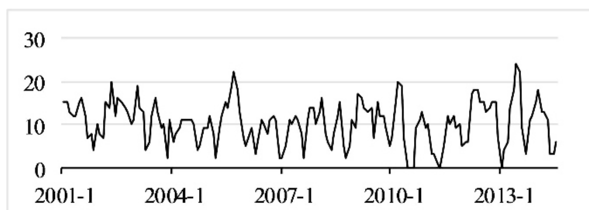

Fig. 1. Actual demand.

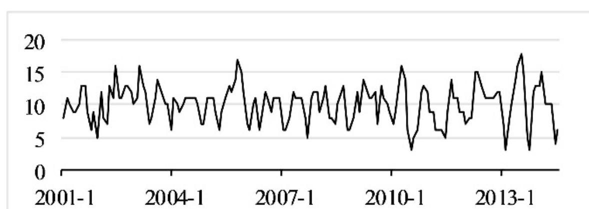

Fig. 2. Result of AR model.

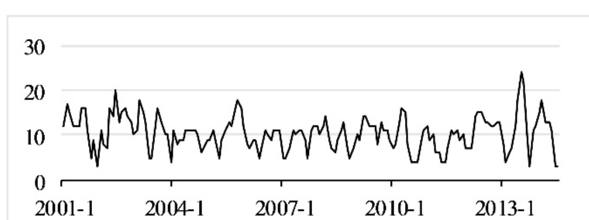

Fig. 3. Result of ARIMA model.

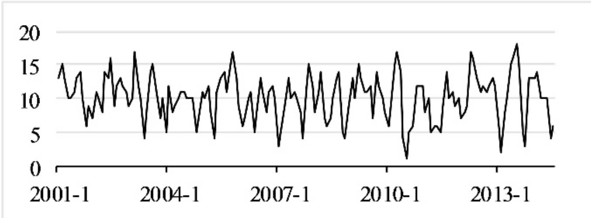

Fig. 4. Result of Automatic arima model.

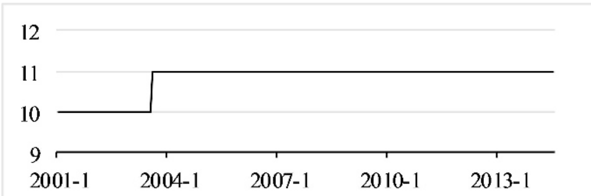

Fig. 5. Result of GM(1,1) model.

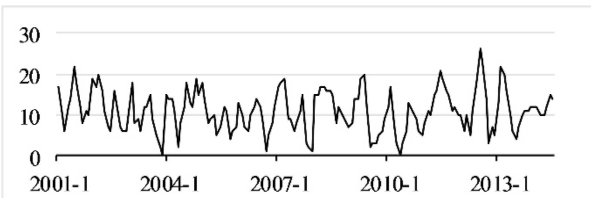

Fig. 6. Result of holt-winters model.

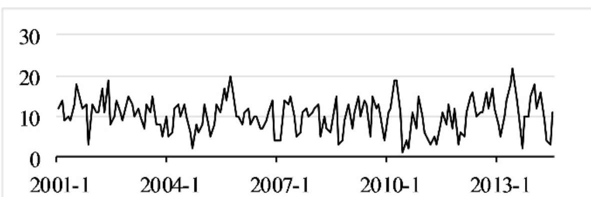

Fig. 7. Result of linear regression model.

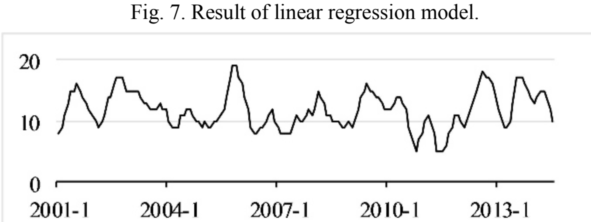

Fig. 8. Result of Poisson model.

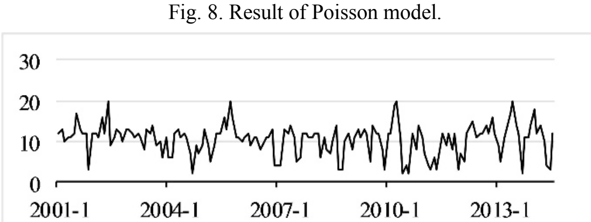

Fig. 9. Result of SVR model.

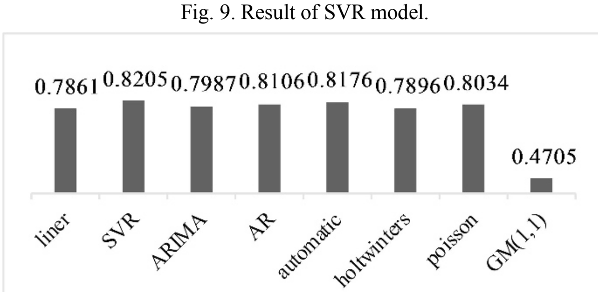

Fig. 10. Grey comprehensive correlation degree-December, 2011

B. Evaluation results of grey comprehensive correlation degree

In this paper, the grey comprehensive correlation degree is used to evaluate the prediction models. Taking the calculation process of the grey comprehensive correlation degree in December 2011 for example, the specific analysis process is as follows.

(1) Select the actual demand of the material *A* and the results of eight prediction models.

(2) Set the weight of grey absolute correlation degree and grey relative correlation degree to 0.5.

(3) Get the grey comprehensive correlation degree, as shown in the Fig.10.

According to the order of the grey comprehensive correlation degree from large to small, it shows that the prediction effect of the support vector machine regression model outperform other forecasting models in December 2011. The predictive effect of Automatic ARIMA model is worse than support vector machine regression model, but it is better than other models. The effect of grey forecasting model GM(1,1) is the most unsatisfactory, which is consistent with the conclusion of the last section.

(4) Obtain the forecast record according to the threshold of the grey correlation degree

According to the characteristics of aircraft demand and the requirement of aircraft management, set the threshold value of the grey comprehensive correlation degree to 0.8. Set the prediction model as an alternative model, whose grey comprehensive correlation degree is more than 0.8. The forecast record in December 2011 is as follows:

$$\{A, SVR, AR, Automatic-ARIMA, Poisson\} \tag{10}$$

C. The association rules between the aircraft material types and prediction models

According to the relationship between material types and alternative prediction models, the confidence level is set to 0.8, and the support level is set to 0.5. The following association rules can be obtained by mining the forecast records from February 2001 to July 2014 which contains 162 monthly forecast records.

According to the association rules obtained from the TABLE II, it can be known that the applicability of Automatic ARIMA model is higher than other forecast models for material A, and the second is the support vector machine regression model. The enterprise will be able to directly select the Automatic ARIMA model to predict the future demand of material A, which can greatly improve the efficiency of the demand prediction.

IV. CONCLUSION

In this paper, we analyzed the problems of aircraft material demand forecasting, and summarized the 8 kinds

TABLE II
ASSOCIATION RULES

NO	Association rules	Support	Confidence
1	{A} => { Automatic ARIMA}	0.74	0.92
2	{A} => { SVR}	0.55	0.85

of demand forecasting models. Then, the grey comprehensive correlation degree between the predicted results of each model and the actual consumption is calculated. According to the threshold value of the grey comprehensive correlation degree, the forecast model was selected, and the forecast record was obtained. Finally, the apriori algorithm is introduced in the paper, and the association rules between the aviation material type and the prediction models were obtained by mining the forecast records. In the future, the optimal forecasting model can be directly given according to the association rules and the type of aviation material, which greatly improves the efficiency of the demand forecasting.

In this paper, the grey comprehensive correlation degree is used to evaluate the eight prediction models. Although it makes up for some deficiencies of absolute degree of grey incidence and the relative degree of incidence, there is not a reliable basis about how to determine the weight between the grey absolute correlation and the relative, which is mainly adjusted according to the experience and historical data. In future studies, we will focus on the weight, so that it can be determined more scientific standards.

ACKNOWLEDGMENT

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Research on the Selection of Business-to-Customer e-commerce Logistics Model Based on Analytic Hierarchy Process Method

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Abstract- **In recent years, Business-to-Customer (B2C) e-commerce has become one of the largest e-commerce transaction models. As an important link in the e-commerce transactions, logistics has an increasing impact on e-commerce. Analysis for enterprise logistics mode becomes particularly important. This paper analyzes the domestic e-commerce transaction scale changes in recent years by using Analytic Hierarchy Process (AHP) to study factors which affecting logistics, and ultimately proposes a new approach to help companies choose their own suitable logistics model .**

Keywords- **AHP, B2C, e-commerce, logistics model**

I. Introduction

Currently, the development of Business-to-Consumer (B2C) e-commerce faces three bottlenecks which are network security, online payment and logistics distribution[1]. With the rapid development of computer technology and the third-party payment platform, the former two problems have been improved. How to choose a proper logistics distribution model is still a big problem. Logistics distribution as "the last mile" of B2C commerce e-commerce is an important part of the user experience[2,3]. This paper develops a practical approach for the selection problem of B2C e-commerce Logistics Model.

II. Development of E-Commerce

With the development of IT Industry, e-commerce has been becoming the most popular business model and even to be almost omnipresent in people’s life, and will continue to develop at a faster speed. According to a survey in 2014, the number of Internet users in main land China has reached 632 million. The e-commerce market has reached 12.3 trillion RMB. The per capita consumption is nearly about 20,000 RMB, 21.3% more than that of 2013. See Fig. 1 for e-commerce transaction size during 2011-2014.

B2C, Business-to-Consumer e-commerce model, one of the most important e-commerce sales models, has been rising in recent years. As shown by iResearch report in the third quarter of 2013, China's Internet market transaction estimated at 454.76 billion RMB, of which 36.6% belonged to B2C model. As Fig.2 shows, the transaction size of China's online shopping in the first quarter of 2012 to the third quarter of 2013.

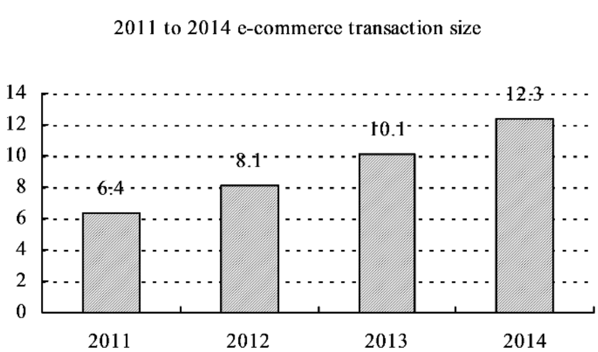

Fig.1 2011 to 2014 e-commerce transaction size

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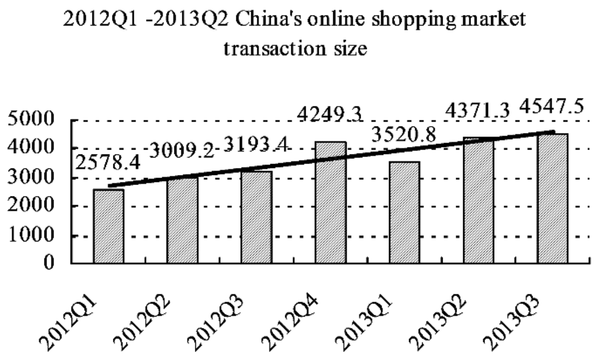

Fig.2 2012Q1 -2013Q2 China's online shopping market transaction size

III. Alternative logistics models of B2C

By a summarization and detailed analysis on the basis of above statistics, we can see that B2C market transaction scale is huge in recent years, and therefore results in a corresponding increase in the number of transactions. So how to choose a suitable logistics mode becomes an urgent and important issue with top priority. Such a logistics and distribution model can not only help cost saving in terms of business running and production for the enterprises, but also improve relationships & cooperation between enterprises and consumers[4]. Consumer spending will also be promoted.

Logistics and distribution model will directly affect the company's sales performance as an important hub between businesses and consumers. At present, most enterprises of B2C e-commerce model mainly adopt three types of logistics models as bellows.

A. Third-party Logistics Model

So called third-party logistics model is that the product supply-side sign contract with a third party Logistics Company who will professionally deliver materials to the demand-side. This mode mainly occurs in e-commerce transactions. Compared with traditional logistics, the third party logistics model is more faster and efficient and also cost saving. Whereas, the only side-effect is that over-reliance on this distribution model will weaken the contact and relations between businesses and customers.

B. Company's own Logistics Model

The company’s own logistics model is that the supply-side builds own delivering system to accomplish its materials distribution. Currently, there are two kinds of e-commerce enterprises using this type of logistic model. One kind is the newly emerging relatively large professional e-commerce companies which provide logistics services for the demand side through a scientific logistics management systems to reduce product costs. The other is the traditional large-scale manufacturing factories which build their own e-commerce sales system, and their own logistics model for material distribution. By this way, the supply-side can directly contact with the demand-side so as to complete the transactions much more coordinated and simpler.

C. Logistics Alliance Model

Logistics Alliance Model is something like a strategic logistics cooperation among supply-side, demand-side and professional logistic company on the basis of mutual benefit. A formal cooperation agreement among the three sides will be signed to achieve a win-win situation.

IV. Logistics Hierarchy Model

Analytic Hierarchy Process (AHP) is a kind of method trying to more effectively solve a complex problem by analyzing the related various factors which can be divided into different levels through systematic and hierarchical analysis in order to find the key factors. Generally the problem to be resolved can be put into three levels, the first layer is the target layer (Goal) which corresponding to the logistics mode selection G; the second layer is criterion layer (Norm) that is the factor layer which corresponding to the middle part of Fig.3 (the third layer F1-F8[5,6]; the final layer is the scheme layer (Scheme) which is the feasible option to

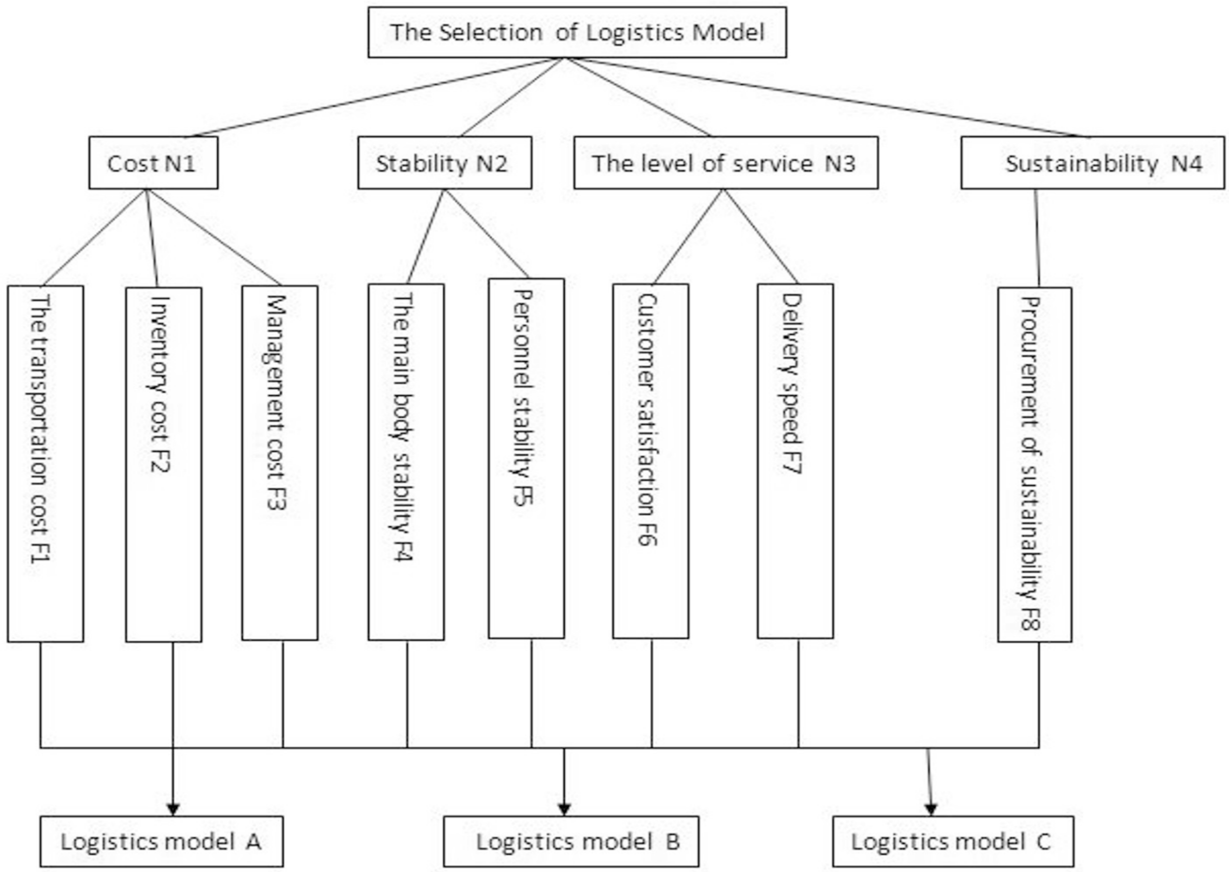

Fig.3 Logistics Hierarchy Model

solve this complex problem, corresponding to Fig.3 in the final layer.

After the systematically analysis so as to select the best logistics mode of B2C for the enterprises, we finally determine the following criteria: (1) Choose the lowest logistics costs as much as possible[7]; (2) Higher stability needed for the logistics[8]; (3) Logistics service qualification to meet the customer's requirements[9,10]; (4) Sustainability of the logistic services and long term good cooperation with customer[11].

Finally, we can get the hierarchical model as Fig.3 shows after decompose the factors of each criterion.

V. Selection of the optimal logistics model by AHP

Hierarchical model built in the previous section total has four criteria (N1-N4) and eight impact factors (F1-F8).The first step is to determine the weights of the four criteria as bellows:

TABLE I

CRITERIA LAYER MATRIX ELEMENT

Norm	N1	N2	N3	N4
N1	N11	N12	N13	N14
N2	N21	N22	N23	N24
N3	N31	N32	N33	N34
N4	N41	N42	N43	N44

In the Table I, Nij represent the degree of importance Ni relative to Nj, e.g. N12 = 3 indicates N1 is 3 times important than N2. To determine the weight of each index weight coefficient, we can use the eigenvector method in this article, see equation (1):

$$N\omega = \lambda_{\max}(t) \qquad (1)$$

Where N is the judgment matrix .Substituting it back into the matrix after obtained the largest eigenvalue ($\lambda_{\max}$) of the matrix N, then calculation the eigenvectors of the matrix N , eventually seeking the weight of each features vector in whole features vector, finally get the weights of all indicators in four criterions:

$$M_N = \omega_N = [\omega_1^N, \omega_2^N, \omega_3^N, \omega_4^N]^T \quad (2)$$

In the same manner, the corresponding weights of factor layer (F1-F8) in Fig.3 can be calculated:

$$M_F = \omega_F = [\omega_1^F, \omega_2^F, \omega_3^F, \omega_4^F, \omega_5^F, \omega_6^F, \omega_7^F, \omega_8^F]^T \quad (3)$$

We can use the feature vector method to find A, B, C three logistics model right corresponding weight of each factor after received the weigh of the criteria and factor. The following example is to calculate customer satisfaction with three corresponding logistics model weight:

TABLE II

MATRIX ELEMENTS OF CUSTOMER SATISFACTION TABLE

Logistics	L1	L2	L3
L1	L11	L12	L13
L2	L21	L22	L23
L3	L31	L32	L33

In the Table II, Nij represents that logistics mode Li is important than Lj for the degree of customer satisfaction photogenic.

With the above methods, we can obtain the largest eigenvalue and eigenvectors about different logistics pattern to F6 (the degree of customer satisfaction). In the same way, determine the largest eigenvalues and eigenvectors other modes of different logistics relative to each factor, then combine the eigenvectors of each factor into decision matrix M_L:

$$M_L = \begin{array}{c} L1 \\ L2 \\ L3 \end{array} \begin{bmatrix} \omega_{11}^L & \omega_{12}^L & \omega_{13}^L & \omega_{14}^L & \omega_{15}^L & \omega_{16}^L & \omega_{17}^L & \omega_{18}^L \\ \omega_{21}^L & \omega_{22}^L & \omega_{23}^L & \omega_{24}^L & \omega_{25}^L & \omega_{26}^L & \omega_{27}^L & \omega_{28}^L \\ \omega_{31}^L & \omega_{32}^L & \omega_{33}^L & \omega_{34}^L & \omega_{35}^L & \omega_{36}^L & \omega_{37}^L & \omega_{38}^L \end{bmatrix} \quad (4)$$

In the formula (4), ω_{ij}^L represents the degree of importance that the impact factors j of the logistics mode i. Eventually, the calculation of the total score for each vector of logistics mode, calculated as follows:

$$D = M_L M_F = [L1 \quad L2 \quad L3]^T \quad (5)$$

The resulting maximum value corresponding to the logistics business model is the best alternative distribution model.

VI. CONCLUSION

With the increase of B2C business volume and sales revenue, the logistics mode of economic efficiency of enterprises become increasingly important. In this paper, logistics model of AHP method has been successfully used, and then presents a new algorithm for logistics models' selection. Organizations can select a suitable model referred to the method discussed in this paper in order to save production cost and provide better logistic services.

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Content Framework and Evaluating Method of the Energy Efficiency Assessment Standard for Machining period

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Abstract - **Energy efficiency assessment is the precondition of energy optimization of machining period, and a set of standardized energy efficiency assessment system can help the optimization of machining period; therefore, the energy efficiency assessment standard for machining period is studied, and the content framework and evaluating method of energy efficiency assessment standard of machining period are proposed. The first step of the evaluating method is to establish the mathematic model of energy efficiency assessing standard, including the energy equation and power equilibrium equation of machining, which are the theoretical basis of the standard; the second step is to set up the energy efficiency assessing indexes including energy utilization ratio and specific energy consumption; the third step is to give the method for obtaining energy efficiency assessing indexes based on the combination of off-line basic data acquiring and on-line input power monitoring. The case study shows that the energy efficiency indexes can be gotten by the proposed evaluating method with enough precision, and only input power of the machining period should be monitored on the site. The results can support the energy efficiency assessment and optimization of machine tools and work-pieces.**

Keywords – **machining, energy efficiency assessment, content framework, evaluating method**

I. INTRODUCTION

Machining is a kind of operation using cutting machine to change the shape, size or performance of work-piece, including turning, drilling, boring, milling, planing, slotting, sawing, broaching, grinding, finishing, gear machining, thread machining and so on [1]. Energy Efficiency of Machining Period (EEMP) is the quantitative expression of effective use ratio of machining period [2]. Evaluating the Energy Efficiency of Machining Period (EEEMP) is to analyze and measure the energy efficiency of machining period.

Recently, many researchers and companies have paid attention on EEMP issue. For example, the Environmentally Benign Manufacturing (EBM) research group at the Massachusetts Institute of Technology (MIT) studies the energy consumption model and energy efficiency calculation model of machine tools; the Laboratory for Manufacturing And Sustainability (LMAS) at University of California, Berkeley focuses on the energy efficiency monitoring system of machining period; the Institute for control engineering of machine tools and manufacturing units at Stuttgart University researches the energy efficiency modeling and simulation of machining period. In addition, Rockwell Automation released the white paper named “the Manufacturing Execution System (MES) used to achieve the sustainability: Expand the scope of MES to achieve energy efficiency and sustainability” in 2009, and energy efficiency improvement of manufacturing process was recognized as a new aim of MES in this white paper [3].

In conclusion, the EEMP issue catches people’s eyes. And we can find that the current researches emphasis on energy efficiency modeling [4-5], energy efficiency analysis and improvement [6-7], etc. Few study about energy efficiency assessment standard of machining period has been carried out.

Energy efficiency assessment is the precondition of energy efficiency improvement of machining period, and set up a standardized energy efficiency assessment system can support the energy efficiency improvement of machining period. Until now, there is not international or national standard about EEEMP, excepting some energy efficiency assessment standards for certain typical products. For example, the International Organization for Standardization (ISO) published the international standard ISO 14955-1:2014 “ Machine tools -- Environmental evaluation of machine tools -- Part 1: Design methodology for energy-efficient machine tools” on 13th May, 2014 [8]. This standard would influence on the machine tool industry greatly as we can see. What is more, some organizations also implement energy efficiency assessment and have formed their own assessing system, such as the Industrial Assessment Centers (IACs) established by Energy Department of the USA. IACs aim to improve the energy efficiency and productivity of a plant site by in-depth assessment of its energy consumption and energy efficiency following a five step industrial assessment protocol [9].

Summarily, EEMP issue is hot and some energy efficiency standards about certain products have published, but the energy efficiency assessment standard for machining period is absent, especially the researches about the mathematical model of the energy efficiency assessment standard for machining period, the index selection and the index acquiring of the energy efficiency assessment standard for machining period. Therefore, the content framework and evaluation method of energy efficiency assessment standard for machining period are studied in this paper with the financial support of the National High-Tech. R&D Program of China (863 Program).

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II. CONTENT FRAMEWORK OF ENERGY EFFICIENCY ASSESSMENT STANDARD FOR MACHINING PERIOD

The use of energy efficiency assessment standard is to give a standardized work instruction for evaluators. The energy efficiency assessment standard should include energy mathematical model, energy efficiency index and the acquiring method of energy efficiency index. Hence, the content framework of energy efficiency assessment standard for machining period is proposed as shown in Fig.1.

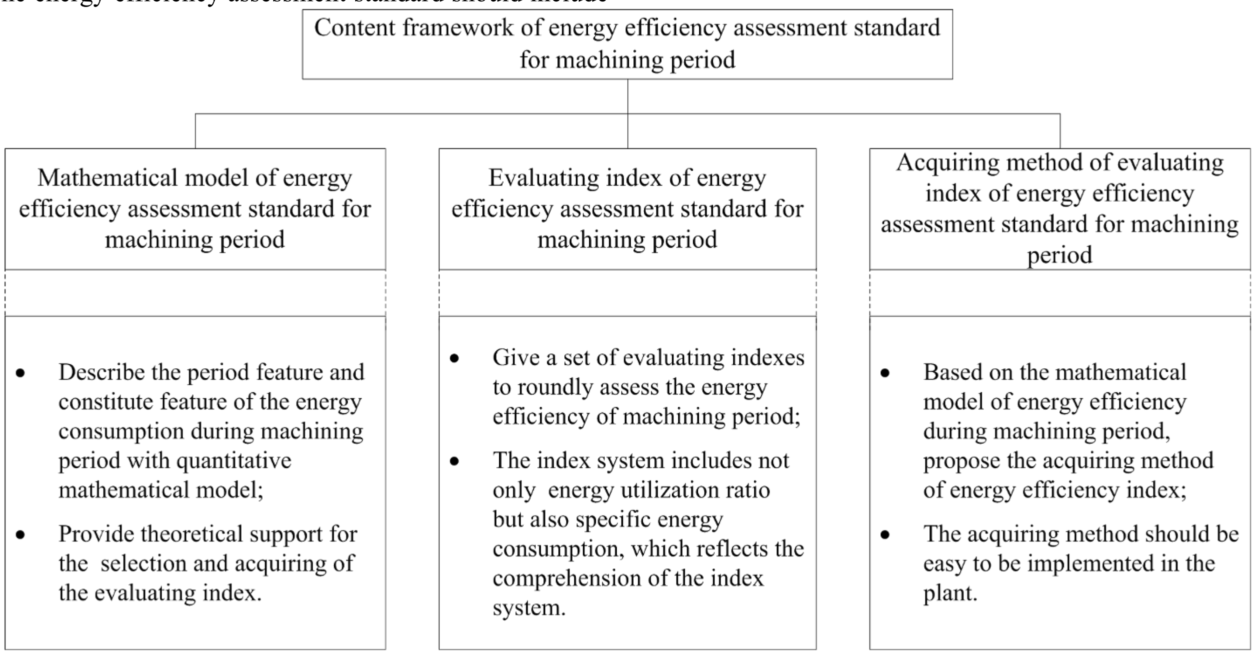

Fig.1 The content framework of energy efficiency assessment standard for machining period

In Fig.1, the mathematical model of energy efficiency assessment standard for machining period is the theoretical basis, which supports the energy efficiency analysis and quantization. With the theoretical basis, the application content of energy efficiency assessment standard can then be implemented, i.e. the selection of evaluating index and the acquiring of evaluating index.

The content framework just gives us a guideline to understand the energy efficiency assessment standard for machining period. And then the three contents in the content framework will be explained further in the following sections.

Ⅲ MATHEMATICAL MODEL OF ENERGY EFFICIENCY ASSESSMENT STANDARD FOR MACHINING PERIOD

To establish the mathematical model of energy efficiency assessment standard for machining period, we should know the energy breakdown of the machining period at first, and then propose the energy equation and power equilibrium equation of machining period.

A. The drawing of energy consumption during machining period

View from the period feature of machining period, the machining period can be divided into four kinds of periods, which are starting period, unload period, cutting period and break period [10]. One kind of period may appear multiple times during a machining period. A drawing of the energy consumption of one machining period is shown in Fig.2.

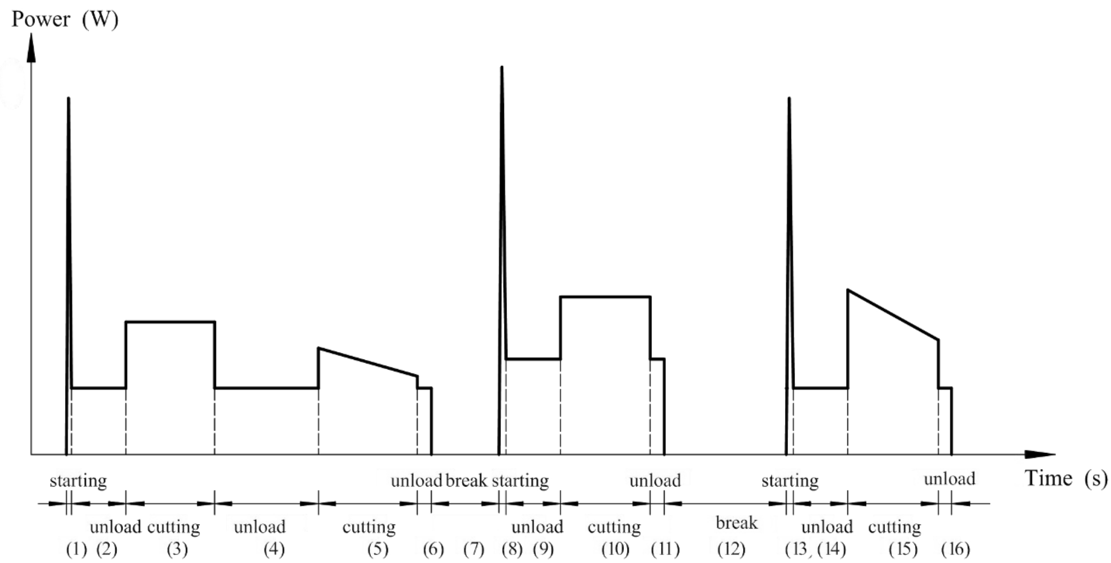

Fig.2 The drawing of energy consumption of a machining period [10]

B. Energy equation of machining period

Refer to section A, the energy equation of machining period can be expressed by (1).

$$E_t = E_s + E_u + E_C + E_b \tag{1}$$

Where,

E_t ——the total energy of the machining period;

E_s ——the total energy of all starting periods;

E_u ——the total energy of all unload periods;

E_C ——the total input energy of all cutting periods;

E_b ——the total energy of all break periods.

C. Power equilibrium model of machining period

(1) Power equilibrium diagram of machining period

The power equilibrium diagram during the machining period is shown as Fig.3. Particularly, the cutting power during the starting, unload and break periods should be zero.

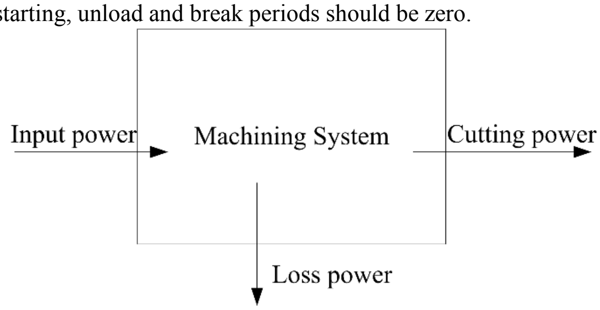

Fig.3 Power equilibrium diagram of machining period

(2) Power equilibrium equation of machining period

① Power equilibrium equation during the cutting period of machining period

The power equilibrium equation during the cutting period of machining period can be expressed as (2).

$$P_{in} = P_c + P_u + P_a \tag{2}$$

Where,

P_{in} ——input power of the machining system;

P_c ——cutting power;

P_u ——unload power of the machining system;

P_a ——additional load loss power of the machining system.

② Power equilibrium equation during the other periods of machining period

During the starting, unload and break periods, the cutting power is zero, and the input power is equal to the loss power.

Ⅳ THE EVALUATING INDEX OF THE ENERGY EFFICIENCY ASSESSMENT STANDARD FOR MACHINING PERIOD

EEMP is the quantitative expression of effective energy use ratio of machining period. Usually, energy efficiency is thought to be the ratio of effective energy to input energy, namely energy utilization ratio. In this paper, energy efficiency can be defined as the ratio of input energy to effective output as well, which is named specific energy consumption.

A. Energy utilization ratio

Energy utilization ratio is the ratio of effective energy to the total input energy during one machining period or a certain period of time. And it can be expressed by (3).

$$\mathrm{E_e} = \frac{E_c}{E_t} \tag{3}$$

Where,

$\mathrm{E_e}$ ——energy utilization ratio;

E_c ——the total cutting energy of all cutting periods.

B. Specific energy consumption

Specific energy consumption (SEC) is the ratio of total input energy to effective output during the machining period, which can be expressed as (4).

$$S_e = \frac{E_t}{E_o} \tag{4}$$

Where,

S_e ——specific energy consumption;

E_o ——effective output, including material removal volume, number of work-piece and so on.

V. ACQUIRING THE EVALUATING INDEX OF THE ENERGY EFFICIENCY ASSESSMENT STANDARD FOR MACHINING PERIOD

A. Acquiring the energy utilization ratio

(1) Acquiring the total input energy

The total input energy can be monitored by the power meter installed at the energy input port of the machining system. We can monitor the input energy of the whole shift period or a machining period of a work-piece.

(2) Acquiring the cutting energy

It is easy to obtain the cutting power during the machining period in laboratory through measuring the cutting force and rotating speed of the main spindle. However, in the plant, it is not practical and un-allowed to install cutting force sensor at the cutting area of the machine tool usually. Therefore, the cutting power is difficult to obtain in real time. Based on our research before, one acquiring method of cutting energy based on off-line basic energy data and real-time input power of the machining system is proposed [4]. The cutting energy can be calculated by quadratic linear regression or simple linear regression with the input power from real-time monitoring, and unload power and additional load loss coefficients from off-line measuring. The calculation equations are shown as (5) and (6).

$$\begin{aligned} E_c &= \int_0^{t_T} P_c(t)\,dt = \sum_{i=1}^{Q_C} E_{ci} = \sum_{i=1}^{Q_C} \int_0^{t_{Ci}} P_c(t)\,dt \\ &= \sum_{i=1}^{Q_C} \int_0^{t_{Ci}} \frac{-a_{1i} + \sqrt{a_{1i}^2 + 4a_{2i}\left[P_{in}(t) - P_{Ui}\right]}}{2a_{2i}}\,dt \end{aligned} \tag{5}$$

$$\begin{aligned} E_c &= \int_0^{t_T} P_c(t)\,dt = \sum_{i=1}^{Q_C} E_{ci} \\ &= \sum_{i=1}^{Q_C} \int_0^{t_{Ci}} P_c(t)\,dt = \sum_{i=1}^{Q_C} \int_0^{t_{Ci}} \frac{P_{in}(t) - P_{ui}}{a_i}\,dt \end{aligned} \tag{6}$$

Where,

a —simple load loss coefficient;

a_1 —quadratic load loss coefficient 1;

a_2 — quadratic load loss coefficient 2;

i — serial number of period;

t_T — total time of the machining period;

Q_C —total number of cutting period;

t_{Ci} —time consumption during cutting period i.

(3) Calculating the energy utilization ratio

The energy utilization ratio of a cycle time and a work-piece can be calculated respectively. The former is the ratio of the total cutting energy to the total input energy during a cycle time, and the latter is the ratio of the cutting energy to the total input energy for machining a work-piece.

B. Acquiring the specific energy consumption

(1) Acquiring the total input energy

With the same method mentioned in Section A, the total input energy for calculating the specific energy consumption index can be got.

(2) Acquiring the effective output

The number of finished work-piece can be counted through observing or automatic counter. And the material removal volume can be calculated by the ratio of cut weight to material density, where the cut weight is gotten by weighting the raw material and the machined work-piece.

(3) Calculating the specific energy consumption

The specific energy consumption of a cycle time and a work-piece can be calculated respectively. The former is the ratio of total input energy to the finished work-piece number or the material removal volume during a cycle time. The latter is the ratio of the total input energy to the material removal volume for machining a work-piece.

VI. CASE STUDY

To verify the energy efficiency standard introduced above, the energy efficiency of machining a plate-part is evaluated following the standard, and the detailed description of the experiment was given in [10].

A. Evaluating step

(1) Acquiring the cutting energy

As (5) and (6) shown, some basic data should be known before for calculating the cutting energy, including the unload power and load loss coefficients of the machine tool.

There are two ways to set up the unload power function of machine tools. Firstly, we can measure the corresponding unload power of the machine tool under its rating rotating speeds. Secondly, we can get the unload power function by regression analysis based on the statistical unload powers measured under typical rotating speeds of the machine tool. The machine tool used in this case study is grading control machine tool, therefore, the first way is adaptive. It is necessary to notice that we need to measure the unload power function of a machine tool just once, and the energy efficiency evaluation of machining by this machine tool in the future can always use the data.

To acquire the load loss coefficients, multiple set of cutting experiments with different cutting parameters under each grade of rotating speed of the machine tool need be implemented. By measuring the input power and cutting power of each cutting scheme, integrating with the unload power measured in last paragraph, the load loss coefficients can be calculated through simple linear regression or quadratic linear regression. In this case study, three cutting schemes are carried out under each rating rotating speed of the machine tool. And the machining period is separated into cylindrical turning, face turning, inner hole turning and second face turning in sequence. The detailed cutting schemes and measured powers can refer to [10]. As the same as the acquiring of unload powers, the measurement of load loss coefficients is implemented just once, and the energy efficiency evaluation of machining at the machine tool in the future can always use the data.

(2) Acquiring the effective output

The effective output in this case study is material removal volume. According to the cutting parameters of this machining period and the feature of the work-piece, we can calculate that the material removal volume of the machining period is 41069.63mm^3.

(3) Acquiring the total input energy

The input energy is measured by the power sensor HIOKI 3390 which is installed at the energy entrance of the machine tool, and the sampling interval of input power is 20ms.

Through real-time monitoring of the input power during the machining period on the site, the energy consumption drawing of the machining period can be obtained as shown in Fig.2.

B. Result analysis

As Fig.2 shown, there are 16 periods during the whole machining period, and 4 cutting periods distribute among the periods. The sequence number of the 4 cutting periods are 3, 5, 10 and 15. The related date for calculating the energy efficiency index of the machining period are shown in Table I.

TABLE I.
RELATED DATE FOR CALCULATING THE ENERGY EFFICIENCY INDEX OF THE PLATE-PART MACHINING PERIOD

indicator	Quadratic approximate cutting energy (J)	Material removal volume (mm^3)	Quadratic approximate energy utilization ratio	Specific energy consumption (J/mm^3)
value	1.19E+05	41069.63	25.38	11.42

As shown in Table I, the energy utilization ratio and specific energy consumption of the machining period using quadratic linear regression method are 25.38 % and 11.42 J/mm^3 respectively. To verify the results, a torque sensor TQ201 is installed at the cutting area of the machine tool to measure the actual energy utilization ratio. In details, to get the torque and actual rotating speed during the machining period by the torque sensor at first; and then to calculate the actual cutting power with the measured torque and rotating speed; to calculate the energy utilization ratio at last, which is 24.96%. Comparing the estimating result with the actual result, we can find that the error is 1.68%.

V. CONCLUSION

Energy efficiency assessment is the fundament of energy efficiency optimization for machining period. Set up a standardized energy efficiency assessment system is to provide support for energy efficiency optimization for machining period. As a result, the content framework and evaluating method of the energy efficiency assessment standard for machining period are studied in this paper. The evaluating method contains three main parts, which are the energy mathematic model for providing theoretical support, the evaluating index system including energy utilization ratio and specific energy consumption, and the acquiring method for energy efficiency index with monitoring the input power on site.

The case study shows that using the evaluating method proposed in this paper can get the energy efficiency index with small error. The standard can be applied into the energy efficiency evaluating, monitoring and optimization of the machine tool and work-piece, having a broad application prospect.

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Combining Problem and Lecture Based Learning for Production System Modeling and Simulation Course in Industrial Engineering Education

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Abstract - **Production system modeling and simulation is an important technical course of industrial engineering education for undergraduate students. This paper presents an initial implementation of hybrid problem based learning (hPBL) method for the course, which combine problem-based learning (PBL) and lecture based learning (LBL) in teaching and learning process. The learning object and content of the course is introduced. An hPBL curriculum schedule is design for the course within a large classroom environment. The various open end problems of modeling and simulation are formulated for group collaborative learning. During learning procedure, the basic concepts and problem solving steps are introduced at the LBL classes, while the PBL classes focus on solving of selected problems. The hPBL greatly arouses the learning interest and improve the learning efficiency of students. The course is evaluated based on the students' survey. The examination score of hPBL is analyzed and compared with pure LBL classes.**

Keywords – **Industrial engineering education, lecture based learning, problem based learning, production system modeling and simulation**

I. INTRODUCTION

In the new millennium, innovation will be the very important motivation for China development. Besides the technical ability personnel, more and more person with creative thinking ability will be needed. The engineering education must enable students to meet the growing challenges and the increasingly more complex demands for the work. Professional problem-solving skills dealing with uncertainty and interpersonal communication ability are two important qualities for the new era students. However, today's engineering graduates lack these skills and have difficulty applying their fundamental knowledge to problems of practice. This requires that teaching, learning and assessment are conceived in such a way that they provide students with several opportunities to support the development of these competencies [1].

Problem-based learning (PBL) originated in medical education to enable a smoother transition of students into clinical education at hospitals, and prepare them better for professional practice [2]. PBL represents a major shift in educational paradigm to problem-based, process-oriented, discipline-integrated, and student-centered learning in collaborative small groups. The goals of PBL include fostering active learning, interpersonal and collaborative skills, open inquiry, real-life problem solving, critical thinking, intrinsic motivation, and the desire to learn for a lifetime. The traditional lecture-based learning (LBL) method is deductive, which begin with theories and progressing towards application of those theories. The teacher presents information without a discussion of why the mathematical models are being developed and what practical problems they will solve [3].

PBL is a philosophy that has to be adapted to the specific situation of a university and the nature of the discipline or subject field in which it is applied. Problem-based approaches to engineering courses may better prepare engineers for the types of work they will actually perform upon graduation and entry into professional practice. A number of studies have reported engineering implementations of PBL and some have identified challenges that were experienced by the engineering student.

The integration of the PBL method into the overall teaching methodology was implemented within the Department of Electrical Engineering [4]. The role of PBL facilitators and the characteristics of the PBL problems were posed in the courses. The usual way of learning technical knowledge about a microcontroller is by reading relevant handbooks and textbooks. Tse and Chan [5] proposed using the problem-based learning to convey such engineering knowledge. The case study in biomedical materials course [6] showed that students made significant improvements in their problem-solving skills, written communication and self-directed learning, which are defined as the desirable professional engineering skills for engineering students. Sanjeev et al. [7] presented the design and construction of a PBL-based course in materials science at the junior level in a mechanical & aerospace engineering department. They assessed the ability of a PBL course based on longer complex problems to enable students to learn both fundamental knowledge of the subject matter and also problem solving skills and contrast it with outcomes in a traditional lecture based course.

Barrows [2] admitted that varying degrees of PBL are often necessary, given the wide variety of contexts in which the method was attempted. One of the challenges the teachers face when implementing PBL is student resistance and discomfort when transitioning from the traditional curriculum to a PBL curriculum. Therefore a hybrid problem based learning (hPBL) maybe an eclectic choice. More importantly, the studies delivered through a combination of PBL and lecture format also showed a significant improvement of student problem-solving skills [8]. The hybrid model is favored as an attractive model in consideration of time, efforts and resources for its acceptance and implementation. Retention of a significant

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