APEM journal

Advances in Production Engineering & Management **ISSN 1854-6250**
Volume 16 | Number 1 | March 2021 | pp 112–124 Journal home: apem-journal.org
https://doi.org/10.14743/apem2021.1.388 Original scientific paper

Optimization of a multi-objective location model of manufacturing base considering cooperative manufacturing capabilities and service benefits

Sun, J.Z.[a,b,*], **Zhang, Q.S.**[a], **Yu, Y.Y.**[c]

[a]School of Management, Shenyang University of Technology, Shenyang, P.R. China
[b]School of Management, Liaoning Institute of Science and Technology, Benxi, P.R. China
[c]School of Management, Jinan University, Guangzhou, P.R. China

A B S T R A C T

Improving customer satisfaction and shortening the manufacturing cycle have become common concerns of current manufacturers. This paper presents a multi-objective location model considering the maximization of collaborative manufacturing capabilities and service benefits. This method first uses the two dimensions of *customer share* and *market consumption* to segment customers, and identify the weight of various customer groups. Secondly, the space vector model (VSM) is used to calculate the matching between manufacturing capabilities and manufacturing requirements. Then build a multi-objective location model based on the two goals of collaborative manufacturing capabilities and service benefits. Finally, the model was tested with simulation data, which proved the validity and feasibility of the model. According to the simulation results, managers can accurately select the optimal manufacturing base from multiple candidate manufacturing bases with regard to less costs, shorter lead times, better manufacturing capabilities, better service benefits. In this paper, Fuzzy theory, Logit model and VSM are combined to salve the problem of manufacturing base location. Considering resources and service benefits of each manufacturing base, it is helpful to optimize the location of enterprises. From the academic and practical points, this study provides a new perspective for the location problem.

A R T I C L E I N F O

Keywords:
Manufacturing base;
Location model;
Multi-objective model;
Optimization;
Decision-making;
Customer demand preference;
Collaborative manufacturing

**Corresponding author:*
bxsunjianzhu@163.com
(Sun, J.Z.)

Article history:
Received 2 February 2021
Revised 22 February 2021
Accepted 28 February 2021

1. Introduction

Enterprises need to get rid of the traditional production modes in order to meet the needs of the market and customers. Enterprises should form manufacturing alliance with other enterprises in the industry chain to achieve resource integration. The manufacturing enterprise is no longer an independent individual serving for the customer, but multiple manufacturing enterprises form a logical overall manufacturing alliance to jointly serve the demand side of the industrial chain. In the face of diversified and personalized customer demands, it is difficult for a single enterprise's resources and capabilities to adapt to rapidly changing market opportunities [1]. Manufacturing companies form a manufacturing alliance to decompose a complete manufacturing task into several sub-tasks. Each manufacturing company is only responsible for the manufacturing of one sub-task, which can shorten the manufacturing cycle [2]. Marković *et al*. pointed out collaborative manufacturing can improve the market competitiveness of enterprises [3].

At the same time, if enterprises want to maximize sustainable development, they need to identify customer groups. For every customer that an enterprise obtains, it has to pay a certain amount of investment in the past, but the returns brought by customers are not the same. In this regard, enterprises must seek out the customer groups that can bring value-added and lock in high-value customer groups. Fazlollahtabar pointed out that a major challenge in marketing work is to determine the best market, especially in market segmentation. Producers need to find high-value markets in order to bring more profits to enterprises [4]. Market segmentation is widely used in various industries, it can effectively help managers lock in high-value customers. Hajibaba *et al.* studied the impact of tourism on hotel management and subdivided the market [5].

Based on this, this paper proposes a location model of manufacturing bases in collaborative manufacturing environment, and studies from two aspects of maximizing the matching degree of collaborative manufacturing capabilities and maximizing service benefit. Firstly, the utility theory of Logit model is used to classify the customers (demand points) in the demand area. The customers are divided into Loyal customers, Problem customers, Gold customers and Taurus customers. According to the production situation, these four types of customers are given different weights. Secondly, the vector space model is used to measure the matching degree between the manufacturing capabilities of collaborative manufacturing partners and the manufacturing demands of customer. Finally, a multi-objective optimization model is established under the constraints of time, cost, collaborative ability and service benefit.

2. Literature review

2.1 Customer segmentation and location decision

Target marketing strategy is an important subject that has attracted much attention from the industry and academia. Market segmentation is a widely used method to study customer purchasing behavior [6]. Tan *et al.* studied the customer's personalized demands and the product structure. He believes that customer behavior affects the manufacturer's planning of candidate product module variants and the production strategy of personalized modules [7]. Wu *et al.* put forward a framework model reflecting enterprise customized production, which combines with organization information processing theory, three-dimensional concurrent engineering theory and resource dependence theory [8]. Han took professional conference organizers as research objects [9]. Zheng *et al.* studied the power demand of different regions through market segmentation, which provides a certain reference for the construction of the power industry [10]. According to the USFK base relocation project, Lee conducted the preference analysis on residential demand, location and site elements of the US air force to determine the location of the residential base [11]. Ghorui *et al.* combine with the market demand of consumers, who uses fuzzy analytic hierarchy process (FAHP) and ideal solution similarity ranking fuzzy technology (FTOPSIS) to select the location of shopping center construction [12]. In the parking lot location problem, Jelokhani-Niaraki and Malczewskil consider the interests of stakeholders and other groups, integrates GIS and multi-criteria decision analysis (MCDA) functions into the web platform, and provids an effective multi-criteria spatial decision support system (MC-SDSS) [13].

2.2 Cooperative manufacturing and location decision

In the industrial revolution, the production and operation system constantly pursues higher efficiency, which causes the manufacturing mode to show two unique characteristics: integrated manufacturing and intelligent manufacturing [14]. Samani *et al.* proposed a concept based on collaborative decision-making, using Analytic Hierarchy Process (AHP) and geographic social networks to select the location of public parking lots in Tehran [15]. Wang *et al.* studies the collaborative construction of wind farms and power to gas plants and establishes a collaborative location planning mathematical model based on the scenario analysis with the optimization objective of maximizing net investment income [16]. Au *et al.* used the feed forward neural network with error back propagation (EBP) learning algorithm and fuzzy analytic hierarchy process (FAHP) to establish the clothing factory location model [17]. Garcia *et al.* studied enterprise location considering regional accessibility, distance, cost, regional security, regional demand and other factors [18]. Cai *et al.* studied the decision-making problem of chemical selection. Considering the regional background air quality information, the emission of new manufacturing sites and the statistical model of local meteorological conditions, he used Monte Carlo optimization method to optimize the location of new chemical factory [19]. Habibi *et al.* proposed a multi-objective robust optimization model, which considered the impact of users, transfer stations, landfills, recycling plants and waste transport vehicles on the location of domestic waste recycling and disposal facilities [20].

3. Problem description

Aiming at the location model under the collaborative manufacturing environment, this paper studies from the two aspects of manufacturing capabilities and service benefit, involving the two-stage location problem and types of nodes: parts suppliers, manufacturing partners, manufacturing enterprises and customers (demand points). Assuming that there are d demand points in the area. To better meet customer demands, the enterprise plans to build several factories in this area. After field surveys, it is found that there are a total of m candidate manufacturing bases for the enterprise to choose. At the same time, it is found that there are s parts manufacturing enterprises can be used as collaborative manufacturing partners and l suppliers. The structural analysis model is shown in Fig. 1. Due to the different mechanism of suppliers and collaborative manufacturing partners, this paper only studies the enterprise location model in collaborative manufacturing environment.

Some parameters involved in this paper are defined in order to facilitate the follow-up study.

$S = \{S_1, S_2, \ldots, S_s\}$: A set of collaborative manufacturing enterprises. S_i represents the i-th collaborative manufacturing enterprise, $i = 1,2, \ldots, s$.

$M = \{M_1, M_2, \ldots, M_m\}$: A set of candidate manufacturing bases. M_j represents the j-th manufacturing base, $j = 1,2, \ldots, m$.

$D = \{D_1, D_2, \ldots, D_d\}$: A set of demand points. $D_l$represents the l-th demand point, $l = 1,2, \ldots, d$.

$R = \{R_1, R_2, R_3, R_4\}$: A set of demand point (customer) types. In this paper, customer groups are divided into four types.

$w = \{w_1, w_2, w_3, w_4\}$: A weight set of demand points. The weight set of demand points can be obtained according to the production and operation experience of the enterprise.

p_{ij} represents the distance between the collaborative manufacturing enterprise S_i and the manufacturing base M_j.

p^*_{jl} represents the distance between the manufacturing base M_j and the demand point D_l.

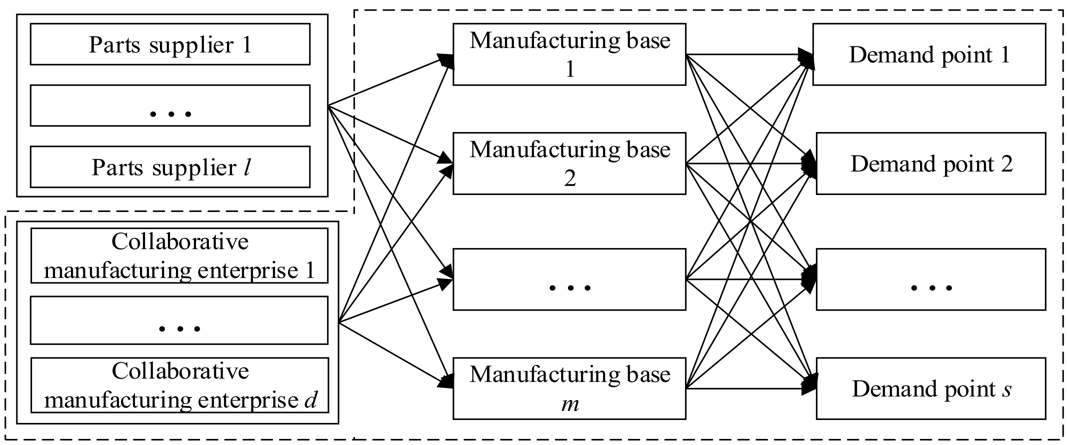

Fig. 1 The structural analysis model of manufacturing base

4. Proposed methodology

4.1 Customer segmentation based on customer value

In this paper, customer value can be interpreted as the present value of the total profits that customers may create for the enterprise in the future, assuming that the customer's current purchasing mode remains unchanged. It can also be understood that after enterprise adjusts operation strategies, the customer's consumption behavior for the product is enhanced, which in turn promotes the increase of corporate profits, and the customer may increase the profit value or revenue value of the enterprise in the future [21]. This paper classifies customer groups according to the two dimensions of *customer share* and *market consumption*, which is called customer classification matrix, as shown in Fig. 2.

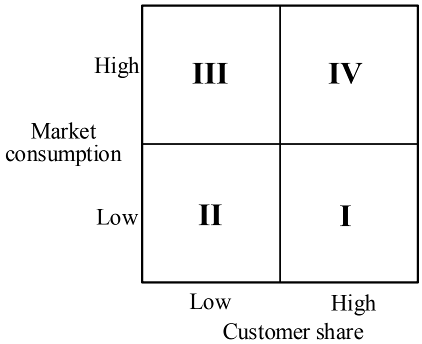

Fig. 2 Customer classification matrix

Market consumption proposed in this paper refers to the total market value of a region for a certain product in a period of time. To a certain extent, market consumption reflects the size and trend of regional demand for production. The demand of manufacturing products is mainly affected by regional economic factors (x_1), regional political and legal factors (x_2), regional information technology factors (x_3), regional cultural factors (x_4), regional customer group factors (x_5). Using the linear regression model, we get the linear regression prediction model of the total market consumption of product in the region, as follow

$$R = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + e \tag{1}$$

Here, a and e are structural parameters. The value of structural parameters has a direct impact on market consumption. In order to get more objective customer segmentation results, this paper uses the entropy method to study the structural parameters in Eq. 1. The specific steps are as follows.

Step 1: Selecting experienced professionals to form an expert group and using the 1-5 scoring method to evaluate the factors of the regional development status. Based on this, we can obtain the evaluation information and establish the evaluation matrix as follow.

$$EA = \begin{bmatrix} a_{11} & \cdots & a_{15} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{n5} \end{bmatrix}_{n\times 5} \tag{2}$$

Here, a_{ik} is the score of the k-th index by expert *i*, $k = 1,\ldots,5$.

Step 2: Calculating the proportion of the k-th index given by expert *i.*

$$\hat{a}_{ik} = \frac{a_{ik}}{\sum_{i=1}^{n} a_{ik}} \;, k = 1,\ldots,5 \tag{3}$$

Step 3: Calculating the entropy value of the k-th index

$$e_k = -\rho \sum_{i=1}^{n} \hat{a}_{ik}\, ln(\hat{a}_{ik}) \tag{4}$$

Here, $\rho = \frac{1}{ln\, n}$, n is the total number of experts, $e_k \geq 0$.

Step 4: Calculating the coefficient of variance of the k-th index

$$de_k = 1 - e_k \tag{5}$$

Step 5: Calculating the weight of each index.

$$\ddot{a}_k = \frac{de_k}{\sum_{k=1}^{5} de_k} \tag{6}$$

According to the index weight, the total market consumption of regional products is further predicted by Eq. 7.

$$R = \sum_{k=1}^{5} \ddot{a}_k x_k \tag{7}$$

Here, x_k is the mean value of the evaluation information.

According to the random utility theory in Logit model [22, 23], the expected utility of an enterprise's products or services can be composed of two parts: decision part and random part, as shown in Eq. 8.

$$ET_l = v_l + e_l \tag{8}$$

ET_l is the expected utility of product j, v_l is decision utility. e_l is random utility. Assuming there are C_n similar products in the market, $l \in [1, C_n]$.

According to the research results of Guadagni and Little, customer choice inertia is also an important factor influencing customer choice [24]. Therefore, the expected utility model can be further expressed as

$$ET_{lg} = v_{lg} + e_{lg} + \xi Last_{lg} \tag{9}$$

Here, ET_{lg} is utility of product h, when customers choose to purchase product l last time. ξ is the customer's purchase inertia coefficient. If $l = g$, $Last_{lg} = 1$. If $l \neq g$, $Last_{lg} = 0$.

Decision utility v_l is determined by a series of related variables.The decision utility can be calculated by Eq. 10.

$$v_l = \sum_{k=1}^{N} \alpha_k x_{lk} \tag{10}$$

Here, x_{lk} is the known observation value, and α_k is the weight coefficient. Comprehensiving Eqs. 9 and 10, the probability of choosing product h can be expressed as Eq. 11.

$$p_{lg} = \frac{e^{\xi Lasg + e_{lg} + \sum_{k=1}^{N} \alpha_k x_{lk}}}{\sum_{g=1}^{Cn} e^{\xi Last_{lg} + e_{lg} + \sum_{k=1}^{N} \alpha_k x_{lk}}} \tag{11}$$

The Markov prediction method can effectively predict the state that may appear in a certain time according to the current state. Markov method predicts that the customer's selection probability of product *l* at the *t*-th time is as follow.

$$(B_{1t}, B_{2t}, \cdots, B_{C_n t}) = (A_1, A_2, \cdots, A_{C_n}) \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1C_n} \\ p_{21} & p_{22} & \cdots & p_{2C_n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{C_n 1} & p_{C_n 2} & \cdots & p_{C_n C_n} \end{pmatrix}^t \tag{12}$$

B_{lt}represents the customer's choice probability of product l for the t-th time, and A represents the current selection probability.

4.2 Manufacturing capabilities matching

In the actual manufacturing process, it is difficult for manufacturing enterprises to obtain real and accurate manufacturing information of collaborative manufacturing partners. Fuzzy theory is considered to be an effective tool to solve the problem of uncertainty and fuzziness [25]. In this paper, triangular fuzzy numbers are used to obtain manufacturing capabilities of manufacturing partners.

$\hat{k} = (k^s, k^m, k^l)$ is a triangular fuzzy number, $k^s \leq k^m \leq k^l$, which membership function $u_{\hat{k}}(x)$ is shown as follows:

$$u_{\hat{k}}(x) = \begin{cases} \frac{x}{k^m - k^s} - \frac{k^s}{k^m - k^s}, x \in [k^s, k^m] \\ \frac{x}{k^m - k^l} - \frac{k^l}{k^m - k^l}, x \in [k^m, k^l] \\ 0, \qquad\qquad\qquad \text{other} \end{cases} \tag{13}$$

In this paper, five level linguistic variables $U = \{VB, B, M, G, VG\}$ are given to describe manufacturing capabilities of manufacturing partners. The corresponding triangular fuzzy numbers are shown in Table 1.

Table 1 Linguistic variables and triangular fuzzy numbers

Language variables	Symbol	Triangular fuzzy number
Very bad	VB	(0,0.1,0.2)
Bad	B	(0.2,0.3,0.4)
Medium	M	(0.4,0.5,0.6)
Good	G	(0.6,0.7,0.8)
Very good	VG	(0.8,0.9,1)

Vector space model (VSM) [26] is used to evaluate the matching degree of manufacturing demands and manufacturing capabilities.

Definition 1: manufacturing capabilities demand vector represents the manufacturing capabilities required for product manufacturing. Let $d = (d_1, d_2, \dots, d_d)$ represents the demand vector. d_j is the j-th product manufacturing demand, $j = 1,2, \dots, d$. The manufacturing capabilities vector of the i-th collaborative manufacturing partner is $m_i = (m_{i1}, m_{i2}, \dots, m_{id})$. m_{ij} is the mastery of j-th manufacturing capabilities by the i-th manufacturing partner, $i = 1,2, \dots s$.

Definition 2: manufacturing capabilities matching degree refers to the matching degree between manufacturing demands and manufacturing capabilities. Product manufacturing demand vectors are definite value. manufacturing capability vectors are obtained by triangular fuzzy number.

If m_{ij} is $\dot{k} = (\dot{k}^s, \dot{k}^m, \dot{k}^l)$, the triangular fuzzy number can be transformed into a definite value by Eq. 14.

$$m_{ij} = \frac{\dot{k}^s + 4\dot{k}^m + \dot{k}^l}{6} \tag{14}$$

According to VSM, the matching degree between manufacturing demands and manufacturing capabilities can be obtained by Eqs. 15 and 16.

$$\text{sim}(M, s_i) = \cos(d, m_i),\ i = 1,2, \dots s \tag{15}$$

$$\cos(d, m_i) = \frac{\sum_{j=1}^{d}(d_j \times m_{ij})}{\sqrt{\sum_{j=1}^{d} d_j^2} \times \sqrt{\sum_{j=1}^{d} m_{ij}^2}}, i = 1,2, \dots s \tag{16}$$

Here, the higher the value of $\text{sim}(M, s_i)$, the higher the matching degree.

4.3 Manufacturing base choice model

This paper gives a multi-objective optimization decision-making model for the manufacturing base. The first goal is to maximize the matching value, that is, the reliability of collaborative manufacturing alliance formed between the candidate manufacturing base and the collaborative manufacturing enterprises. The second objective is to maximize the service benefits under the customer preference, that is, the satisfaction degree of each candidate manufacturing base to the customer demand of different regions.

According to the characteristics of purchasing, production, transportation and sales of manufacturing enterprises, collaborative manufacturing mainly involves four influencing factors: cost, time, demand and collaboration.

The total production and operation costs of candidate manufacturing base M_j are divided into construction costs (c^1), transportation costs (c^2) and manufacturing costs (c^3). Among them, transportation cost (c^2) includes parts transportation cost (c_{ij}^2) and finished product distribution cost (c_{jl}^2).

$$C_j = c_j^1 + c_j^2 + c_j^3 \tag{17}$$

$$c_j^2 = \sum_{i=1}^{s} c_{ij}^2 + \sum_{l=1}^{d} c_{jl}^2 \tag{18}$$

In order to facilitate the study, this paper stipulates that the unit transportation cost is the same, which is expressed as $\hat{c}$, then the Eq. 18 can be expressed as:

$$c = \hat{c}\left(\sum_{i=1}^{s} p_{ij} + \sum_{l=1}^{d} p_{jl}^*\right) \tag{19}$$

The times of the manufacturing base M_j is the sum of the collaborative manufacturing times (t^1) and the delivery times (t^2), which can be expressed by Eq. 20.

$$T_j = \sum_{i=1}^{s} t_{ij}^1 + \sum_{l=1}^{d} t_{jl}^2 \tag{20}$$

Full coverage and joint coverage are selected to study the collaborative manufacturing capabilities. It is required that the collaborative manufacturing capabilities must meet the minimum manufacturing capabilities (Z_j) of manufacturing bases.

$$\sum_{i=1}^{s} g\left(p_{ij}\right) \geq Z_j \tag{21}$$

Among them, $g\left(p_{ij}\right)$ is the collaborative manufacturing capabilities based on distance factor under the situation of full coverage, which can be calculated by Eq. 22.

$$g(p_{ij}) = \begin{cases} \mathrm{sim}\left(M_j, s_i\right), p_{ij} \leq r \\ 0, p_{ij} > r \end{cases} \quad i = 1,2,\ldots,s, j = 1,2,\ldots,m \tag{22}$$

Here, r is the full coverage radius.

Gradual coverage and joint coverage are selected to study the effective service of demand points. The sum of services of manufacturing base is required to meet the minimum service demands (Z_l^*) of each demand point.

$$\sum_{j=1}^{m} g\left(p_{jl}^*\right) \geq Z_l^* \tag{23}$$

Among them, $g\left(p_{jl}^*\right)$ are the service capacity based on distance factor in the context of gradual coverage, which can be calculated by formula (30).

$$g(p_{jl}^*) = \begin{cases} Q_i; p_{jl}^* \leq r_1 \\ Q_i - p_{jl}^*; r_1 < p_{jl}^* \leq r_2 \\ 0; r_2 < p_{jl}^* \end{cases} \quad i = 1,2,\ldots,s, j = 1,2,\ldots,m \tag{24}$$

Here, Q_i is the service capacity of i regions. r_1 is the full coverage radius. r_2 is the maximum service radius that can be perceived.

According to the previous analysis, this paper constructs a multi-objective optimization location model for manufacturing bases.

$$\max\ Z = \sum_{j=1}^{m} \mathrm{sim}\left(M_j, s_i\right) x_j \tag{25}$$

$$\max\ U = \sum_{l=1}^{d} w_l \sum_{j=1}^{m} g\left(p_{jl}^*\right) x_j \tag{26}$$

$$s.t.\ \sum_{j=1}^{m} g\left(p_{jl}^*\right) x_j \geq Z_l^* \tag{27}$$

$$\sum_{i=1}^{s} g\left(p_{ij}\right) x_j \geq Z_j \tag{28}$$

$$\sum_{j=1}^{m} x_j \left(c_j^* + \hat{c}\left(\sum_{i=1}^{s} p_{ij} + \sum_{l=1}^{d} p_{jl}^*\right)\right) \leq C \tag{29}$$

$$\sum_{j=1}^{m} x_j\left(\sum_{i=1}^{s} p_{ij} + \sum_{l=1}^{d} p_{jl}^*\right) \leq T \tag{30}$$

$$Z_l^* \geq 0;\ \ Z_j \geq 0;\ \ c_j^* \geq 0;\ \ p_{jl}^* \geq 0;\ \ p_{ij} \geq 0 \tag{31}$$

$$x_j = \begin{cases} 0; & M_j \text{ is selected} \\ 1; & M_j \text{ is not selected} \end{cases} \tag{32}$$

Eq. 25 represents the maximum matching value. Eq. 26 represents the maximum service benefit. Eq. 27 is the service benefit constraint. Eq. 28 is the collaborative manufacturing capabilities constraint. Eq. 29 is the cost constraint. Eq. 30 is time constraint. Eqs. 31 and 32 express the value range of decision variables.

5. Results and discussion

5.1 Results

An equipment manufacturing enterprise A plans to build several factories in city B. According to the product sales records, 40 product demand points are obtained. Through the survey of the city, 18 candidate sites were obtained for site selection. At the same time, it was discovered that 20 manufacturing enterprises could act as collaborative manufacturing partners. According to the location model proposed in this paper, firstly, it is necessary to segment the customer groups for these 40 product demand points.

Four experienced professionals in the industry and six enterprise employees were selected to form an expert group. The 1-5 scoring method is adopted to evaluate the status quo of regional development and index weights, which evaluation information as shown in Table 2.

Table 2 Regional evaluation information (one demand point)

	Development status evaluation					Index weight evaluation				
	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5
Experienced professionals	4	2	4	4	5	3	1	5	4	3
	3	2	5	3	5	4	3	5	1	1
	5	4	5	5	1	1	2	2	5	1
	3	5	2	3	2	1	1	5	3	1
Enterprise employees	2	1	5	2	5	2	4	3	3	1
	2	3	4	5	5	2	1	2	1	1
	2	1	4	5	1	5	1	4	3	5
	4	4	3	5	4	5	3	5	5	4
	4	2	3	2	5	3	2	4	2	1
	2	1	1	1	3	3	1	4	1	3

According to the evaluation information, the evaluation matrix EA is established. Furthermore, the proportion matrix $\hat{a}$ of each expert for each index is calculated.

$$EA = \begin{bmatrix} 3 & 1 & 5 & 4 & 3 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 3 & 1 & 4 & 1 & 3 \end{bmatrix}_{10\times 5}$$

$$\hat{a} = \begin{bmatrix} 0.103 & 0.053 & 0.128 & 0.143 & 0.143 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.103 & 0.053 & 0.103 & 0.036 & 0.143 \end{bmatrix}$$

Using the entropy method, the weight of each index can be calculated, as shown below.

$$de = (0.051,0.062,0.020,0.063,0.095)$$

$$\ddot{a} = (0.176,0.212,0.069,0.217,0.326)$$

According to Eq. 7, the total market consumption of regional products is predicted as follows.

$$R = \sum_{k=1}^{5} \ddot{a}\, x = 3.257$$

According to field investigation, it is found that there are three kinds of similar products in this area. The evaluation information of customers for these four products is obtained in the form of questionnaire survey, as shown in Table 5. According to the random utility theory, the expected utility (ET) of each product is calculated.

Table 3 The expected utility (ET) of each product (one demand point)

Products		Determining utility (v)	Random utility (e)	Inertia coefficient (ξ)	Expected utility(ET)	
					$l \neq g$	$l = g$
Product 1 (A enterprise)		4	2	0.332	6	6.332
Similar products	Product 2	4	3	0.402	7	7.402
	Product 3	3	5	0.152	8	8.152
	Product 4	2	5	0.114	7	7.114

Based on the Markov prediction method, the selection probability of the next purchase of the demand point is predicted by using the Eqs. 11 and 12.

$$B = (0.331,0.404,0.157,0.109)$$

We can know the market share of enterprise A is 0.331. We can use the same method to calculate market share of other demand points, as shown in Fig. 3.

According to Fig. 3, there are 9 Loyal customers, 9 Problem customers, 10 Gold customers and 12 Taurus customers in 40 demand points. In the next production and operation reform, the influence weights of four types of customers on enterprise production are 0.05, 0.15, 0.45 and 0.35 respectively, that is $w = (0.05,0.15,0.45,0.35)$.

According to production requirements, enterprise A outsources the five sub-manufacturing processes of equipment manufacturing products and provides the minimum product manufacturing capacities requirements, $d = (0.419,0.502,0.562,0.516,0.441)$. Based on the experiences, an expert group was invited to use fuzzy theory to evaluate the manufacturing capabilities. According to Table 1, the manufacturing capabilities evaluation information of the collaborative manufacturing partner is obtained, as shown in Table 4.

The mean value of the triangular fuzzy number is obtained by the mean value method, and then, the triangular fuzzy number is converted into a certain value. The collaborative manufacturing capabilities vector m_i of collaborative manufacturing partners is shown in Table 5.

The matching degree is calculated, as shown in Table 6.

In order to ensure the smooth delivery of products, the manufacturing capabilities matching degree ≥ 0.9 is selected to participate in the product manufacturing process. s_3, s_4, s_6, s_{11} are selected. The total collaborative manufacturing capabilities of enterprise A is 11.428. The collaborative manufacturing capacity of 18 candidate manufacturing bases is shown in Table 7.

The 40 product demand points, 20 collaborative manufacturing partners and 18 manufacturing enterprise candidate points are scaled down and drawn on the plane of [0,100]×[0,100]. The location relationship and information are shown in Fig. 4 and Table 8.

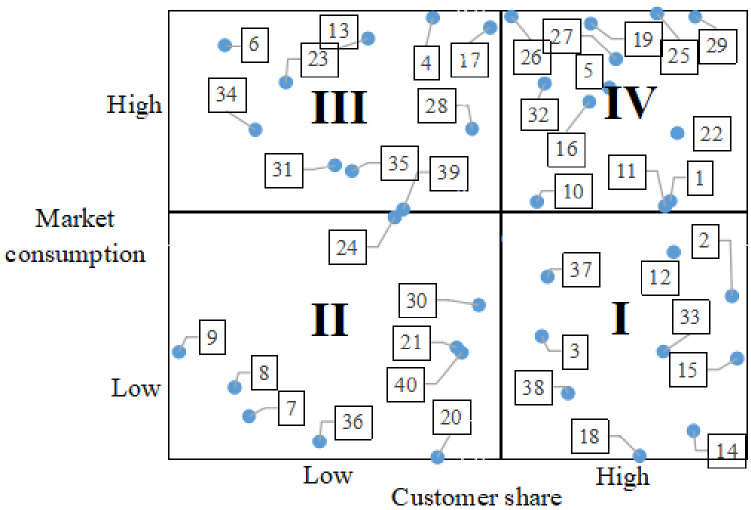

Fig. 3 Demand points subdivision graph

Table 4 Fuzzy value of manufacturing capacity (one expert)

	m_i				
	m_{i1}	m_{i2}	m_{i3}	m_{i4}	m_{i5}
s_1	(0.8,0.9,1)	(0.4,0.5,0.6)	(0.2,0.3,0.4)	(0,0.1,0.2)	(0.8,0.9,1)
s_2	(0.2,0.3,0.4)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.8,0.9,1)	(0.6,0.7,0.8)
s_3	(0,0.1,0.2)	(0.6,0.7,0.8)	(0.4,0.5,0.6)	(0.2,0.3,0.4)	(0.6,0.7,0.8)
s_4	(0.8,0.9,1)	(0.6,0.7,0.8)	(0.4,0.5,0.6)	(0.8,0.9,1)	(0.6,0.7,0.8)
s_5	(0.6,0.7,0.8)	(0.6,0.7,0.8)	(0,0.1,0.2)	(0.8,0.9,1)	(0.4,0.5,0.6)
s_6	(0.4,0.5,0.6)	(0.2,0.3,0.4)	(0.8,0.9,1)	(0.6,0.7,0.8)	(0,0.1,0.2)
s_7	(0,0.1,0.2)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.2,0.3,0.4)	(0.8,0.9,1)
s_8	(0.8,0.9,1)	(0.8,0.9,1)	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0.8,0.9,1)
s_9	(0.6,0.7,0.8)	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0,0.1,0.2)
s_{10}	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0.2,0.3,0.4)	(0.4,0.5,0.6)	(0.8,0.9,1)
s_{11}	(0.6,0.7,0.8)	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.4,0.5,0.6)	(0.6,0.7,0.8)
s_{12}	(0,0.1,0.2)	(0.8,0.9,1)	(0.2,0.3,0.4)	(0.2,0.3,0.4)	(0.6,0.7,0.8)
s_{13}	(0.2,0.3,0.4)	(0.8,0.9,1)	(0.2,0.3,0.4)	(0.8,0.9,1)	(0.4,0.5,0.6)
s_{14}	(0.6,0.7,0.8)	(0.6,0.7,0.8)	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0,0.1,0.2)
s_{15}	(0,0.1,0.2)	(0.8,0.9,1)	(0.2,0.3,0.4)	(0.8,0.9,1)	(0.6,0.7,0.8)
s_{16}	(0.2,0.3,0.4)	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0.2,0.3,0.4)	(0.4,0.5,0.6)
s_{17}	(0.8,0.9,1)	(0.8,0.9,1)	(0,0.1,0.2)	(0.2,0.3,0.4)	(0.8,0.9,1)
s_{18}	(0.6,0.7,0.8)	(0,0.1,0.2)	(0.8,0.9,1)	(0.6,0.7,0.8)	(0.2,0.3,0.4)
s_{19}	(0.6,0.7,0.8)	(0.8,0.9,1)	(0.4,0.5,0.6)	(0.2,0.3,0.4)	(0.4,0.5,0.6)
s_{20}	(0.6,0.7,0.8)	(0.4,0.5,0.6)	(0.4,0.5,0.6)	(0.6,0.7,0.8)	(0.8,0.9,1)

Table 5 Collaborative manufacturing capabilities

	m_i		m_i
s_1	$m_1 = (0.314,0.752,0.224,0.691,0.849)$	s_{11}	$m_{11} = (0.076,0.728,0.514,0.968,0.965)$
s_2	$m_2 = (0.533,0.629,0.788,0.482,0.765)$	s_{12}	$m_{12} = (0.478,0.019,0.273,0.622,0.035)$
s_3	$m_3 = (0.397,0.945,0.976,0.188,0.802)$	s_{13}	$m_{13} = (0.457,0.528,0.811,0.466,0.238)$
s_4	$m_4 = (0.481,0.108,0.835,0.513,0.438)$	s_{14}	$m_{14} = (0.317,0.578,0.536,0.364,0.624)$
s_5	$m_5 = (0.701,0.141,0.426,0.261,0.772)$	s_{15}	$m_{15} = (0.348,0.025,0.076,0.138,0.569)$
s_6	$m_6 = (0.103,0.194,0.621,0.408,0.131)$	s_{16}	$m_{16} = (0.324,0.204,0.690,0.640,0.654)$
s_7	$m_7 = (0.915,0.651,0.668,0.772,0.850)$	s_{17}	$m_{17} = (0.646,0.518,0.195,0.676,0.971)$
s_8	$m_8 = (0.753,0.337,0.490,0.323,0.947)$	s_{18}	$m_{18} = (0.193,0.828,0.850,0.769,0.407)$
s_9	$m_9 = (0.391,0.408,0.271,0.480,0.376)$	s_{19}	$m_{19} = (0.375,0.586,0.852,0.439,0.565)$
s_{10}	$m_{10} = (0.892,0.243,0.437,0.952,0.896)$	s_{20}	$m_{20} = (0.403,0.843,0.604,0.748,0.819)$

Table 6 Matching degree (one manufacturing base)

Collaborative enterprises	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9	s_{10}
$sim(M,s_i)$	0.900	0.982	0.913	0.913	0.844	0.876	0.974	0.884	0.974	0.894
Collaborative enterprises	s_{11}	s_{12}	s_{13}	s_{14}	s_{15}	s_{16}	s_{17}	s_{18}	s_{19}	s_{20}
$sim(M,s_i)$	0.899	0.767	0.962	0.970	0.695	0.939	0.886	0.952	0.976	0.974

Table 7 Collaborative manufacturing capabilities of manufacturing base

Manufacturing bases	Collaborative capability	Manufacturing bases	Collaborative capability	Manufacturing bases	Collaborative capability
M_1	11.428	M_7	10.295	M_{13}	9.942
M_2	12.606	M_8	8.455	M_{14}	11.708
M_3	8.537	M_9	10.354	M_{15}	12.803
M_4	11.217	M_{10}	10.537	M_{16}	9.188
M_5	9.526	M_{11}	12.801	M_{17}	7.848
M_6	13.804	M_{12}	10.206	M_{18}	8.758

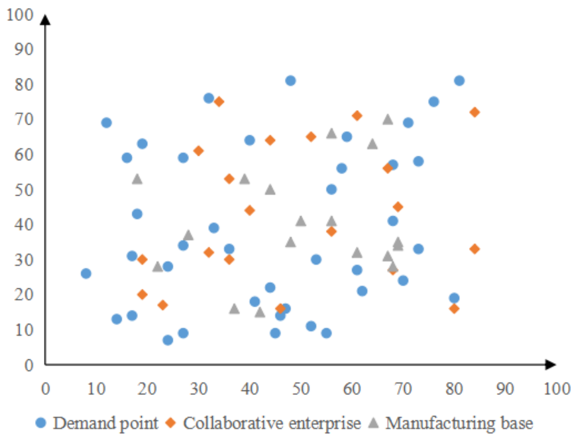

Fig. 4 Location diagram

Table 8 Manufacturing information (A part)

s	r	M	C	T	$g(p)$	$sim(M,s_i)$	Z	$[r_1,r_2]$	D	$g(p^*)$	Z^*	w
s_1	20.569	M_1	19.143	10.603	11.428	11.428	9.513	[30.351,32.393]	D_1	60.566	50.642	0.35
s_2	25.448	M_2	18.127	6.593	12.606	12.606	9.957	[28.689,29.833]	D_2	44.108	58.482	0.05
s_3	28.397	M_3	18.895	5.451	8.537	8.537	6.800	[33.552,35.048]	D_3	60.936	49.063	0.05
s_4	20.312	M_4	20.863	5.217	11.217	11.217	8.481	[28.768,30.501]	D_4	59.558	64.009	0.45
s_5	21.954	M_5	15.484	8.066	9.526	9.526	8.567	[31.658,33.155]	D_5	54.574	31.149	0.35

Based on the above calculation data, the location model is established according to the Eqs. 31 to 39. Assuming that the total cost is no more than 2 million and the delivery time is no more than 25 months, the location model is as follows.

$$\max\ Z = 11.428x_1 + 12.606x_2 + \cdots 7.848x_{17} + 8.758x_{18}$$

$$\max\ \ U = 0.35(60.566x_1 + \cdots 56.564x_{18}) + \cdots 0.15(60.566x_1 + \cdots 56.564x_{18})$$

$$S.t.\ \begin{cases} \begin{cases} 60.566x_1 + 44.108x_2 + \cdots 56.564x_{18} \geq 50.642 \\ \cdots \\ 60.566x_1 + 44.108x_2 + \cdots 56.564x_{18} \geq 66.354 \end{cases} \\ \begin{cases} 11.428x_1 + 12.606x_2 + \cdots 8.758x_{18} \geq 9.513 \\ \cdots \\ 11.428x_1 + 12.606x_2 + \cdots 8.758x_{18} \geq 15.624 \end{cases} \\ 19.143x_1 + 19.552x_2 + \cdots 15.621x_{18} \leq 200 \\ 10.603x_1 + 6.593x_2 + \cdots 9.447x_{18} \leq 25 \\ x_j = \begin{cases} 0; & M_j \text{ is not selected}, j = 1,2,\ldots,18 \\ 1; & M_j \text{ is selected} \end{cases} \end{cases}$$

The location model belongs to 0-1 integer programming model, which is solved by lingo software. According to the solution results, we can choose 4 candidate manufacturing bases (3, 4, 6, 11) to build. These 4 bases can cover all the demand points under the constraints of cost, time, collaborative requirements and service requirements.

5.2 Discussion

Changing time parameter constraints of the model, other parameters remain unchanged, the multi-objective value change trend of the model is shown in Fig. 5. As can be seen from Fig. 5, with the increase of manufacturing time constraint, the collaborative manufacturing capabilities and service benefits are increased. When the time constraint increases to a certain value, the multi-objective value remains constant, which no longer increases with the increase of time. The location problem involves many factors, only relaxing time constraints, which can increase target values within a certain range. But after a certain value, the time factor will no longer affect the target values.

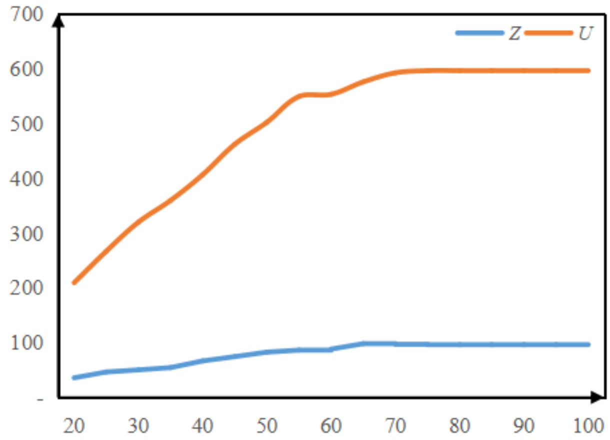

Fig. 5 Time parameter analysis

6. Conclusion

Collaborative manufacturing breaks the traditional manufacturing mode and realizes flexible production. Aiming at the location model of manufacturing base in collaborative manufacturing environment, this paper presents a multi-objective location model considering collaborative manufacturing capabilities and service benefit. Firstly, the Logit model is used to segment the customers and identify the influence weight of various customer groups. Secondly, the space vector model is used to calculate the matching degree between the manufacturing capabilities and the manufacturing demands. Then, a multi-objective location model is established based on the two objectives of collaborative manufacturing capabilities and service benefit. Finally, the simulation data is used to test the model. In this paper, the method considers manufacturing capabilities and service benefits of manufacturing base from a new research perspective, which is closed to the actual manufacturing status and also provides a reference for the subsequence location model. In this paper, the location problem relaxed the constraints of distribution vehicles. In the actual location problem, logistics distribution is also an important problem in the location problem. Therefore, in the next research, scholars should pay attention to the impact of logistics distribution on the location problem.

Acknowledgement

This article was financially supported by Department of Education Science of Liaoning Province in 2020 (Grant No. W2020lkyfwdf-05).

References

[1] Ocampo, L.A., Himang, C.M., Kumar, A., Brezocnik, M. (2019). A novel multiple criteria decision-making approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy AHP for mapping collection and distribution centers in reverse logistics, *Advances in Production Engineering & Management,* Vol. 14, No. 3, 297-322, doi: 10.14743/apem2019.3.329.

[2] Medic, N., Anisic, Z., Lalic, B., Marjanovic, U., Brezocnik, M. (2019). Hybrid fuzzy multi-attribute decision making model for evaluation of advanced digital technologies in manufacturing: Industry 4.0 perspective, *Advances in Production Engineering & Management,* Vol. 14, No. 4, 483-493, doi: 10.14743/apem2019.4.343.

[3] Marković, G., Zdravković, N., Karakašić, M., Kolarević, M. (2020). Modified PROMETHEE approach for solving multi-criteria location problems with complex criteria functions, *Tehnički Vjesnik – Technical Gazette*, Vol. 27, No. 1, 12-19, doi: 10.17559/TV-20190225151515.

[4] Fazlollahtabar, H. (2021). A DSS-based dynamic programming for finding optimal markets using neural networks and pricing, *Iranian Journal of Management Studies,* Vol. 14, No. 1, 87-106, doi: 10.22059/ijms.2020.269091.673397.

[5] Hajibaba, H., Grün, B., Dolnicar, S. (2019). Improving the stability of market segmentation analysis, *International Journal of Contemporary Hospitality Management,* Vol. 32, No. 4, 1393-1411, doi: 10.1108/IJCHM-02-2019-0137.

[6] Chen, Y. (2017). Integrated and intelligent manufacturing: Perspectives and enablers, *Engineering,* Vol. 3, No. 5, 588-595, doi: 10.1016/J.ENG.2017.04.009.

[7] Tan, C., Chung, H., Barton, K., Jack Hu, S., Freiheit, T. (2020). Incorporating customer personalization preferences in open product architecture design, *Journal of Manufacturing Systems,* Vol. 56, 72-83, doi: 10.1016/j.jmsy.2020.05.006.

[8] Wu, Q., Liao, K., Deng, X., Marsillac, E. (2020). Achieving automotive suppliers' mass customization through modlarity: Vital antecedents and the valuable role and responsibility of information sharing, *Journal of Manufacturing Technology Management,* Vol. 31, No. 2, 306-329, doi: 10.1108/JMTM-12-2018-0459.

[9] Han, S.Y. (2016). Convention Market Segmentation by the Attributes of Convention Site Selection – On the Subject of Professional Convention Organizers (PCO), Seoul Studies, Vol. 17, No, 4, 111-129.

[10] Zheng, X., Wu, C., He, S. (2020). Impacts of market segmentation on the over-capacity of the thermal electricity generation industry in China, *Journal of Environmental Management,* Vol. 279, Article No. 111761, doi: 10.1016/j.jenvman.2020.111761.

[11] Lee, H. (2019). Analysis of location and site planning preference of USFK residential housing, *Journal of the Korea Academia-Industrial cooperation Society,* Vol. 20, No. 12, 822-827, doi: 10.5762/KAIS.2019.20.12.822.

[12] Ghorui, N., Ghosh, A., Algehyne, E.A., Mondal, S.P., Saha, A.K. (2020). AHP-TOPSIS inspired shopping mall site selection problem with fuzzy data, *Mathematics,* Vol. 8, No. 8, Article No. 1380, doi: 10.3390/math8081380.

[13] Jelokhani-Niaraki, M., Malczewski, J. (2015). A group multicriteria spatial decision support system for parking site selection problem: A case study, *Land Use Policy,* Vol. 42, 492-508, doi: 10.1016/j.landusepol.2014.09.003.

[14] Yoseph, F., Malim, N.H.A.H., Heikkilä, M., Brezulianu, A., Geman, O., Rostam, N.A.P. (2020). The impact of big data market segmentation using data mining and clustering techniques, *Journal of Intelligent & Fuzzy Systems,* Vol. 38, No. 5, 6159-6173, doi: 10.3233/JIFS-179698.

[15] Samani, Z.N., Karimi, M., Alesheikh, A.A. (2018). A novel approach to site selection: Collaborative multi-criteria decision making through geo-social network (Case study: Public parking), *ISPRS International Journal of Geo-Information,* Vol. 7, No. 3, Article No. 82, doi: 10.3390/ijgi7030082.

[16] Wang, P., Liu, W., Lin, Z., Wen, F., Dong, Z., Zheng, Y., Zhang, R. (2017). Scenario analysis based collaborative site selection planning of wind farms and power-to-gas plants, *Automation of Electric Power Systems,* Vol. 41, No. 6, 20-29, doi: 10.7500/AEPS20161012007.

[17] Au, K.F., Wong, W.K., Zeng, X.H. (2006). Decision model for country site selection of overseas clothing plants, *International Journal of Advanced Manufacturing Technology,* Vol. 29, No. 3-4, 408-417, doi: 10.1007/s00170-005-2505-4.

[18] García, J.L., Alvarado, A., Blanco, J., Jiménez, E., Maldonado, A.A., Cortés, G. (2014). Multi-attribute evaluation and selection of sites for agricultural product warehouses based on an Analytic Hierarchy Process, *Computers and Electronics in Agriculture,* Vol. 100, 60-69, doi: 10.1016/j.compag.2013.10.009.

[19] Cai, T., Wang, S., Xu, Q. (2015). Monte Carlo optimization for site selection of new chemical plants, *Journal of Environmental Management,* Vol. 163, 28-38, doi: 10.1016/j.jenvman.2015.08.002.

[20] Habibi, F., Asadi, E., Sadjadi, S.J., Barzinpour, F. (2017). A multi-objective robust optimization model for site-selection and capacity allocation of municipal solid waste facilities: A case study in Tehran, *Journal of Cleaner Production,* Vol. 166, 816-834, doi: 10.1016/j.jclepro.2017.08.063.

[21] Awaga, A.L., Xu, W., Liu, L., Zhang, Y. (2020). Evolutionary game of green manufacturing mode of enterprises under the influence of government reward and punishment, *Advances in Production Engineering & Management*, Vol. 15, No. 4, 416-430, doi: 10.14743/apem2020.4.375.

[22] Li, H.-Y., Xu, W., Cui, Y., Wang, Z., Xiao, M., Sun, Z.-X. (2020). Preventive maintenance decision model of urban transportation system equipment based on multi-control units, *IEEE Access,* Vol. 8, 15851-15869, doi: 10.1109/ACCESS.2019.2961433.

[23] Shapiro, A.F., Koissi, M.-C. (2017). Fuzzy logic modifications of the analytic hierarchy process, *Insurance: Mathematics and Economics,* Vol. 75, 189-202, doi: 10.1016/j.insmatheco.2017.05.003.

[24] Guadagni, P.M., Little, J.D.C. (2008). Commentary – A logit model of brand choice calibrated on scanner data: A 25th anniversary perspective, *Marketing Science,* Vol. 27, No. 2, 26-28, doi: 10.1287/mksc.1070.0345.

[25] Shao, W., Ding, H., Tang, J., Peng, S. (2018). A data-driven optimization model to collaborative manufacturing system considering geometric and physical performances for hypoid gear product, *Robotics and Computer-Integrated Manufacturing,* Vol. 54, 1-16, doi: 10.1016/j.rcim.2018.05.004.

[26] Jian, J., Wang, M., Li, L., Su, J., Huang, T. (2019). A partner selection model for collaborative product innovation from the viewpoint of knowledge collaboration, *Kybernetes,* Vol. 49, No. 6, 1623-1644, doi: 10.1108/K-05-2018-0266.