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Big Data Supported PSS Evaluation Decision in Service-Oriented Manufacturing

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ABSTRACT Product-service system (PSS) is an effective solution for service-oriented manufacturing. In the life cycle of PSS, evaluation decision of PSS alternatives is of great significance for subsequent implementation. Supported by the big data of stakeholder comments, a PSS evaluation decision technique is explored. Based on the multi-stakeholder comments of PSS evaluation decision's influence factors, the index system considering the environmental effect is constructed through analyzing and summarizing the co-occurrence matrix and semantic network diagram of high-frequency words. To determine the index value of PSS alternative, the stakeholders' vague opinions expressed by trapezoidal fuzzy number are fused. At last, PSS alternatives are evaluated by Kullback-Leibler divergence (KLD) modified TOPSIS. The case of PSS evaluation decision for a printer company shows that the explored technique is effective.

INDEX TERMS Multi-stakeholder comments, co-occurrence matrix, semantic network diagram, trapezoidal fuzzy number, Kullback-Leibler divergence, TOPSIS.

I. INTRODUCTION

With the maturity and application of the new generation of information technology, a new round of industrial revolution is in full swing. The strategic position of manufacturing industry has been attached great importance. In recent years, many countries have formulated and launched their own manufacturing development strategies, such as Germany's "industry 4.0" and "national industrial strategy 2030", EU's "2020 growth strategy", US's "advanced manufacturing Partnership Plan", China's "made in China 2025", etc. Among them, intelligent manufacturing has become the main direction of the industrial revolution and industrial development. In addition, sustainable development has become the consensus of human development. Green development as the most important subset of the sustainable development concept has received special attention. Many countries, organizations and institutions have actively participated in various plans, outlines, agreements or initiatives to protect the ecological environment and promote green economic growth [1]–[3]. Manufacturing industry has a significant contribution to environmental problems, and a new round of industrial

revolution will bring profound and lasting changes to the work and life of employees and users [4].

Service-oriented manufacturing is a new manufacturing mode of integration of manufacturing industry and service industry. In service-oriented manufacturing mode, manufacturing enterprises provide users with integrated solutions of personalized products and services. Product-service system (PSS), which can provide manufacturing enterprises with an overall solution to create high added value by the concordance of visible products and invisible services, emerges as the times require in this context. As a new manufacturing paradigm, the environmental and social impact of PSS is not clear and needs special attention. In particular, due to the fuzziness of customer demand and the understanding deviation of designer to customer demand, the PSS scheme is not unique in the design stage of PSS. The quality of the scheme is directly related to customer satisfaction. In order to better meet the personalized needs of customers and improve the market share of enterprises, it is particularly important to evaluate multiple PSS schemes and achieve PSS evaluation decision optimization.

In recent years, with the emergence of new information publishing methods represented by social networks [15], LBS (location-based services) [16], and the rise of cloud

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computing [17], [18], IoT (Internet of things) [19] and other technologies, data is growing and accumulating at an unprecedented speed, and the era of big data has come [20]. The rapid development of big data technology has a profound impact on social economy and industrial model [21]. Scholars have also begun to apply big data methodology to decision-making process [22]–[24]. Open source data analysis software tools (such as web crawler, text analysis, semantic network diagram, etc.) provide more convenient means for big data mining and reuse. Therefore, these background technologies make big data supported PSS evaluation decision optimization possible.

PSS evaluation decision is essentially a multi-criteria decision-making problem, which mainly includes the steps of index system construction, index value determination and alternatives evaluation.

In the aspect of index system construction, the stakeholders involved in PSS evaluation decision include multiple fields, such as PSS user, user demand analyst, PSS entrepreneur, social and environmental researcher and PSS design engineer. Therefore, the multiple stakeholders should be taken as the perspective of the problem. The existing studies only consider one or two aspects of the index evaluation system construction, and are not comprehensive. It is a common method to obtain source data by publishing topics in the forum, inviting various stakeholders to carry out online discussions, and extracting big data of multi-perspective comments by web crawler software. Many kinds of stakeholders should cover the stakeholders of PSS evaluation decision as much as possible, and can be composed of multiple PSS users, multiple PSS user demand analysts, multiple PSS entrepreneurs, multiple social and environmental researchers and multiple PSS design engineers.

In the aspect of index value determination, multiple qualitative or quantitative factors need to be considered respectively, and the process of index value determination is rather tedious. The mathematical and statistical characteristics of stakeholder scoring method can make the best use of stakeholder experience, and the calculation process is very simple. However, stakeholders' assessment on the relative merits and demerits of multiple PSS on an index depends on personal experience and subjective judgment, so it is unreasonable to express them with accurate values.

In the aspect of alternatives evaluation, the traditional alternatives evaluation methods include TOPSIS, VIKOR, AHP, etc. Among these research, TOPSIS is a classic method for multi-attribute evaluation. In traditional TOPSIS, object's closeness, which is calculated by Euclidean distances between the evaluation object and the two ideal points, is used as the basis of evaluation [40]. However, the objects on the perpendicular bisector of two ideal points have the same closeness and cannot be distinguished by traditional TOPSIS.

To sum up, PSS evaluation decision using general methods is difficult in service-oriented manufacturing. The research gaps are mainly reflected as follows. The index system of PSS evaluation decision is difficult to establish. There are

some problems in the current research, such as the selection of indexes is too subjective and not comprehensive. The determination of index weight mainly depends on subjective or objective weighting method. The former mainly considers the knowledge, experience and preference of decision makers. Although the latter can make up for the deficiency of the former to some extent, it only considers the difference between index values and ignores the correlation between indexes. The complexity of index system leads to the solution of index value is very tedious, and the scalar dimensions of different indexes are different, which cannot be directly used for evaluation.

In view of the above gaps, this article aims at the practical engineering problems in service-oriented manufacturing, explores a big data supported PSS evaluation decision technique. Firstly, the index system considering the environmental effect is constructed through analyzing and summarizing the co-occurrence matrix and semantic network diagram of high-frequency words, which are collected from the multi-stakeholder comments of PSS evaluation decision's influence factors. Secondly, the stakeholders' vague opinions of PSS alternative's performance on evaluation index are expressed by trapezoidal fuzzy number and fused to determine the index value of PSS alternative. Then, TOPSIS is modified by replacing Euclidean distance with Kullback-Leibler divergence (KLD) of information theory, and the modified TOPSIS is adopted to sequence the PSS alternatives.

The remainder of this article is organized as follows: Section II proposes the overall research architecture. Section III constructs the index system of PSS evaluation decision based on big data of stakeholder comments. Section IV determines the index value using vague opinion fusion. Section V evaluate the PSS alternatives by KLD modified TOPSIS. In Section VI, a case study to test the effectiveness of explored PSS evaluation decision technique is presented. Final conclusions are summarized in Section VII.

II. OVERALL RESEARCH ARCHITECTURE

To provide a big data supported technique for PSS evaluation decision, we propose an overall architecture as shown in Fig. 1. The overall architecture is divided into four layers.

The first layer contains multiple stakeholders, which are divided into several categories, such as PSS user, user demand analyst, PSS entrepreneur, social and environmental researcher, PSS design engineer, etc.

The second layer is data layer. By forum topic, online discussion, telephone interview, random investigation and other ways, the big data resource from the perspective of multiple stakeholders is obtained by web crawler tool. By vague assessment, the opinions of alternatives' performance on each index are obtained which are represented by fuzzy numbers.

The third layer is approach layer. To construct the index system, the concept processing and word segmentation processing of the extracted multi-perspective comment big data are implemented with the text analysis software, and the word frequency statistics are executed to get the high frequency

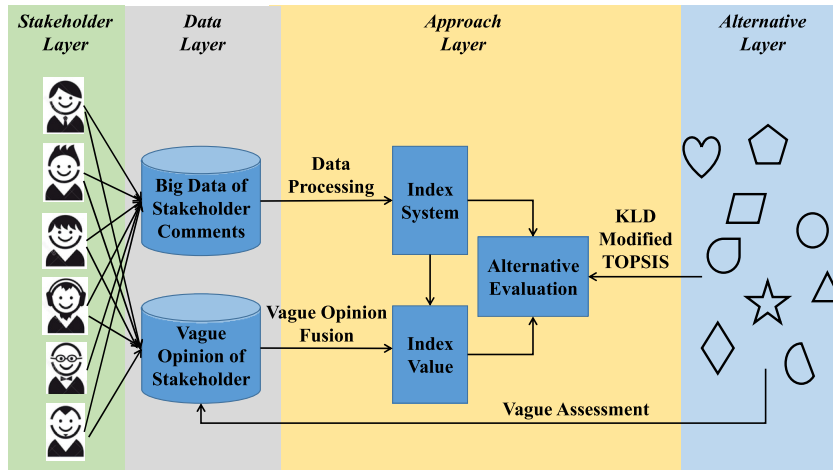


FIGURE 1. Overall research architecture.

TABLE 1. Part of the high-frequency words.

	High-frequency word	Frequency (%)
W1	High service quality	3.39
W2	Product quality standard	3.24
W3	Environment sustainable development	3.21
W4	High degree of technological maturity	3.18
W5	Low resource consumption	3.15
W6	User safety guaranteed	3.08
W7	Stimulating the job market	3.01
W8	Lucrative	2.96
W9	User expectations	2.85
W10	Service quality requirement	2.84
...

word catalogue. Then, the co-occurrence matrix of high frequency words is formed. The index system is constructed based on semantic network graph analysis. To determine the index value, the multiple stakeholders' vague assessment opinions expressed by fuzzy numbers are fused and the index value matrix is obtained. At last, KLD modified TOPSIS is adopted to evaluate the PSS alternatives.

The fourth layer is alternative layer which is composed of several PSS alternatives. After PSS evaluation decision, the best PSS alternative will be obtained, which is of great significance for later implementation of PSS.

III. INDEX SYSTEM CONSTRUCTION BASED ON BIG DATA OF STAKEHOLDER COMMENTS

Web crawler is adopted to obtain multi-stakeholder big data of stakeholder comments about PSS evaluation decision from forum topic, online discussion, user comment and other channels. Next, text analysis is adopted to implement the concept processing and word segmentation processing and execute the word frequency statistics. After eliminating the words with no actual meaning or obvious direction, we screen 83 high-frequency words and obtain the real high-frequency word catalogue. Part of the high-frequency words is shown in Table 1.

The co-occurrence matrix of high-frequency words is used to express the relative relationship between two high-frequency words. The larger the value of the intersection

	W ₁	W ₂	W ₃	W ₄	W ₅	W ₆	W ₇	W ₈	W ₉	W ₁₀	...
W ₁	0	538	113	579	114	151	158	104	603	571	
W ₂		0	167	614	121	177	165	192	635	608	
W ₃			0	122	621	109	113	181	172	135	
W ₄				0	150	153	191	177	567	589	
W ₅					0	118	156	120	134	108	
W ₆						0	142	176	159	166	
W ₇							0	557	121	140	
W ₈								0	131	169	
W ₉									0	676	
W ₁₀										0	
...											

FIGURE 2. Part of the co-occurrence matrix of high frequency words.

of two high-frequency words is, the stronger the correlation between them is. Next, high-frequency word analysis is adopted for the matrix analysis of high frequency word catalogue and the co-occurrence matrix of high frequency words is obtained. Part of the co-occurrence matrix of high frequency words is shown in Fig. 2. The values in Fig. 2 are co-occurrence times.

In addition, social network analysis of high-frequency words is used to obtain the semantic network diagram of high-frequency words. The semantic network diagram of top 30 high-frequency words is shown in Fig. 3.

Based on the co-occurrence matrix shown in Fig. 2 and the semantic network diagram shown in Fig. 3, we summarize and classify the text data of high-frequency words. Then we abstract the high-frequency words with the same attribute according to the logical relationship and mutual relationship, and continuously attempt to categorize the high-frequency words. At last, we classify each high-frequency word into a category. As shown in Fig. 4, the obtained category is the second-level index of PSS evaluation decision. Then we abstract and classify the second-level indexes again, and obtain the first-level indexes. At last, the index

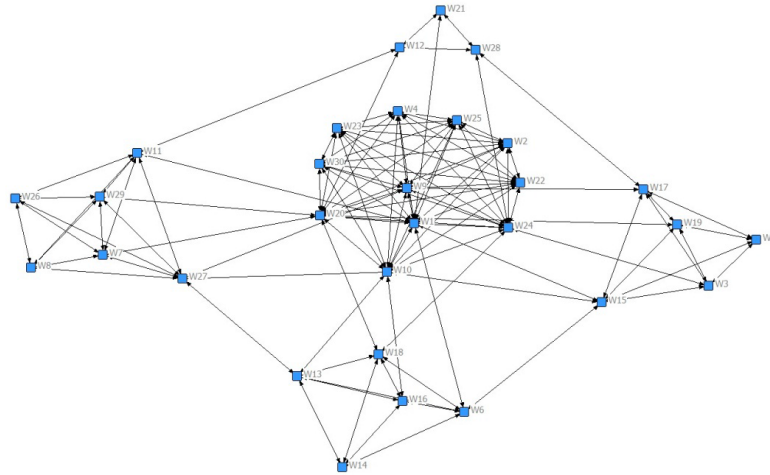


FIGURE 3. The semantic network diagram of top 30 high-frequency words.

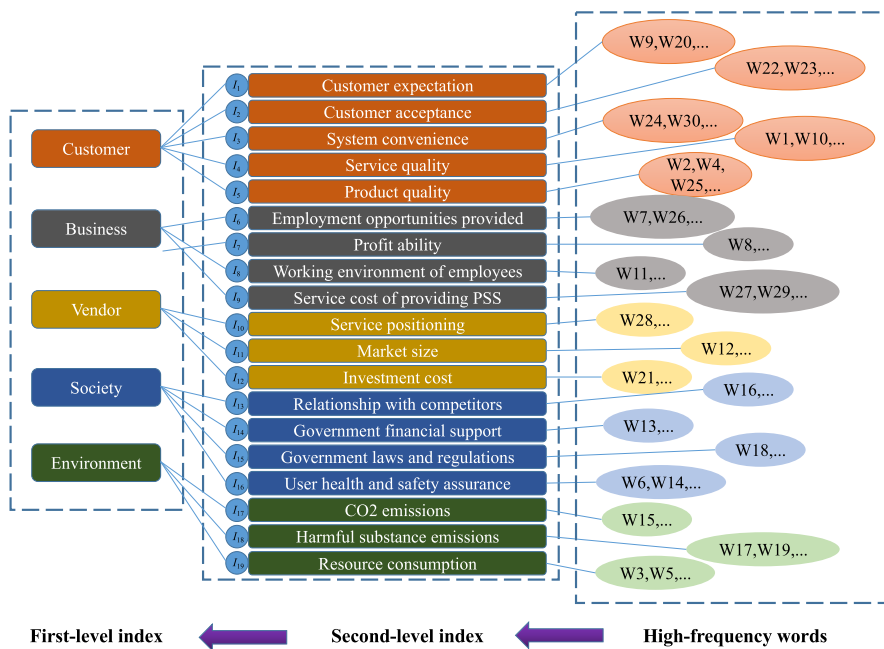


FIGURE 4. The index system of PSS evaluation decision.

system of PSS evaluation decision is constructed as shown in Fig. 4.

IV. INDEX VALUE DETERMINATION USING VAGUE OPINION FUSION

The stakeholder’s assessment opinion of PSS alternative’s performance on one index is vague, and it is more reasonable to use fuzzy number to express the assessment value than accurate value. Two kinds of fuzzy numbers commonly used in fuzzy theory are trapezoidal fuzzy number and triangular fuzzy number. The membership function of trapezoidal fuzzy number is more complex and can simulate the vagueness of stakeholder’s assessment better than triangular fuzzy number. Therefore, trapezoidal fuzzy number is applied in this article to express the stakeholder’s vague assessment on the index value of PSS alternatives. According to the arithmetic

TABLE 2. Corresponding relation of accurate value and fuzzy value in nine-level scale assessment.

Vague comment	Accurate value	Fuzzy value
Extremely good (VC1)	9	(4,17/3,9,9)
Strongly good (VC2)	7	(7/3,3,17/3,9)
Obviously good (VC3)	5	(3/2,13/7,3,4)
Slightly good (VC4)	3	(1,11/9,13/7,7/3)
Middle (VC5)	1	(1,1,1,1)
Slightly bad (VC6)	1/3	(3/7,7/13,9/11,1)
Obviously bad (VC7)	1/5	(1/4,1/3,7/13,3/2)
Strongly bad (VC8)	1/7	(1/9,3/17,1/3,3/7)
Extremely bad (VC9)	1/9	(1/9,1/9,3/17,1/4)

rules of trapezoid fuzzy number, the commonly used nine-level scale assessment comments and values are fuzzed to get the corresponding trapezoid fuzzy number as shown in Table 2.

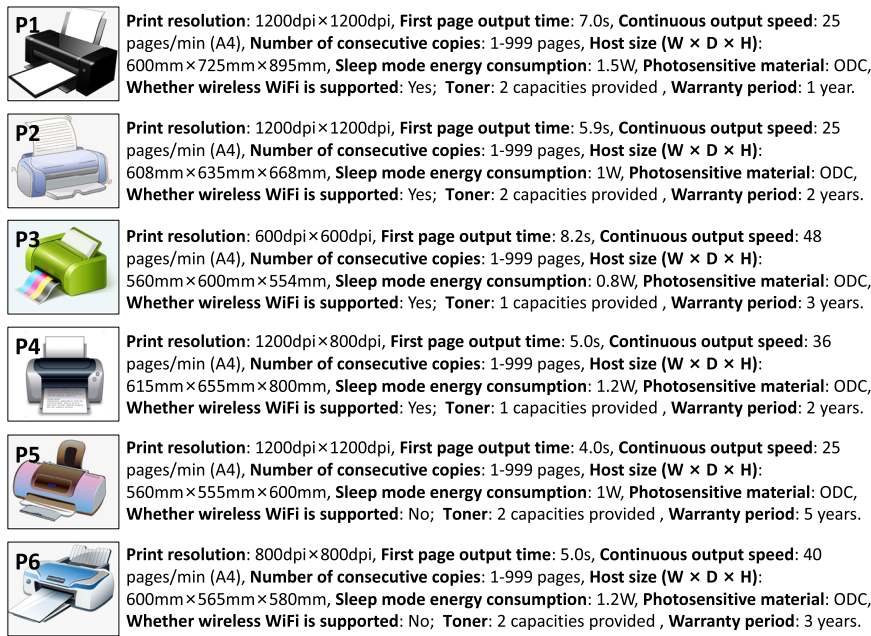


FIGURE 5. Six PSS alternatives (P1, P2, P3, P4, P5 and P6).

There are p PSS alternatives and q stakeholders. According to Table 1, the assessment value of alternative s ($1 \leq s \leq p$) given by stakeholder r ($1 \leq r \leq q$) on index I_i is $\tilde{x}_{s,i}^r = (a_{s,i}^r, b_{s,i}^r, c_{s,i}^r, d_{s,i}^r)$, which is in trapezoid fuzzy number form. Using the arithmetic average method, the group decision assessment value is calculated as follows:

$$\begin{aligned} \tilde{x}_{s,i}^r &= (a_{s,i}, b_{s,i}, c_{s,i}, d_{s,i}) = \left(\sum_{r=1}^q a_{s,i}^r / q, b_{s,i} \right. \\ &= \left. \sum_{r=1}^q b_{s,i}^r / q, c_{s,i} = \sum_{r=1}^q c_{s,i}^r / q, d_{s,i} = \sum_{r=1}^q d_{s,i}^r / q \right) \end{aligned} \quad (1)$$

Then, through the gravity center form of trapezoid fuzzy number, the group decision assessment value is converted into the real number form as follows:

$$x_{s,i} = \frac{(c_{s,i}^2 + c_{s,i}d_{s,i} + d_{s,i}^2) - (a_{s,i}^2 + a_{s,i}b_{s,i} + b_{s,i}^2)}{3(c_{s,i} + d_{s,i} - a_{s,i} - b_{s,i})} \quad (2)$$

$t_{s,i}$ is the index value of PSS alternative s on index I_i . After calculating the index values of all PSS alternatives on each index, the index value matrix is obtained as $X = [x_{s,i}]_{p \times N}$.

V. ALTERNATIVE EVALUATION BY KLD MODIFIED TOPSIS

In information theory, the difference degree between two n -dimensional uncertainty systems $\theta^A = (\theta_1^A, \theta_2^A, \dots, \theta_n^A)$ and $\theta^B = (\theta_1^B, \theta_2^B, \dots, \theta_n^B)$ can be measured by KLD as follows:

$$KLD^{A,B} = \sum_{k=1}^n \left[\theta_k^A \log \frac{\theta_k^A}{\theta_k^B} + (1 - \theta_k^A) \log \frac{1 - \theta_k^A}{1 - \theta_k^B} \right] \quad (3)$$

where θ_k^A and θ_k^B mean the appearance probability of uncertain status k in systems θ^A and θ^B . KLD has the

characteristics as follows: $KLD^{A,B} \geq 0$, and only if $A = B$, $KLD^{A,B} = 0$.

According to index value matrix $X = [x_{s,i}]_{p \times N}$, the index weight is obtained by standard deviation method. The standard deviation of index I_i is as follows:

$$\sigma_i = \sqrt{\frac{1}{n} \sum_{s=1}^p (x_{s,i} - \frac{1}{p} \sum_{s=1}^p x_{s,i})^2} \quad (4)$$

Then the weight of index I_i is obtained as follows:

$$\omega_i = \frac{\sigma_i}{\sum_{i=1}^N \sigma_i} \quad (5)$$

Finally, we obtain the weighted index value matrix $T = [t_{s,i}]_{p \times N}$. Here, $t_{s,i} = \omega_i x_{s,i}$. Therefore, the positive ideal point and the negative ideal point are as follows:

$$\begin{aligned} T^+ &= [t_1^+, t_2^+, \dots, t_i^+, \dots, t_N^+] \\ T^- &= [t_1^-, t_2^-, \dots, t_i^-, \dots, t_N^-] \end{aligned} \quad (6)$$

where $t_i^+ = \max\{t_{1,i}, t_{2,i}, \dots, t_{p,i}\}$ and $t_i^- = \min\{t_{1,i}, t_{2,i}, \dots, t_{p,i}\}$.

The index value of PSS alternative s is expressed as $T^s = [t_{s,1}, t_{s,2}, \dots, t_{s,i}, \dots, t_{s,N}]$ which is the row s of index value matrix $T = [t_{s,i}]_{p \times N}$. Therefore, the KLD from T^s to positive ideal point T^+ is obtained as follows:

$$KLD^{s,+} = \sum_{i=1}^N \left[t_{s,i} \log \frac{t_{s,i}}{t_i^+} + (1 - t_{s,i}) \log \frac{1 - t_{s,i}}{1 - t_i^+} \right] \quad (7)$$

And the KLD from T^s to negative ideal point T^- is obtained as follows:

$$KLD^{s,-} = \sum_{i=1}^N \left[t_{s,i} \log \frac{t_{s,i}}{t_i^-} + (1 - t_{s,i}) \log \frac{1 - t_{s,i}}{1 - t_i^-} \right] \quad (8)$$

TABLE 3. The vague comment statistics of P1.

	V C	V C	V C	V C	V C	V C	V C	V C	V C	VC9
I_1	3	1	5	17	1	9	10	1	3	
I_2	20	2	1	7	6	0	6	0	8	
I_3	5	1	3	12	3	9	5	8	4	
I_4	7	5	4	3	5	1	7	2	16	
I_5	2	10	5	0	3	12	0	4	14	
I_6	1	8	3	2	4	1	14	0	17	
I_7	21	2	13	2	0	4	1	4	3	
I_8	12	4	3	0	12	6	1	7	5	
I_9	7	1	17	2	13	1	1	5	3	
I_{10}	4	6	4	6	3	13	0	2	12	
I_{11}	2	3	0	2	15	0	10	17	1	
I_{12}	31	6	4	1	3	0	1	3	1	
I_{13}	0	10	13	2	5	6	7	4	3	
I_{14}	12	15	2	0	0	5	6	4	6	
I_{15}	4	24	5	1	1	0	7	3	5	
I_{16}	0	5	3	14	7	9	2	6	4	
I_{17}	1	0	6	9	5	6	0	1	22	
I_{18}	2	4	0	1	0	2	12	5	24	
I_{19}	6	17	0	2	1	9	3	6	6	

TABLE 4. The index value of P1.

	Index value (trapezoid fuzzy number form)	Index value (real number form)
I_1	(0.9327,1.1951,1.8770,2.4369)	1.6197
I_2	(2.0311,2.7727,4.3595,4.7067)	3.4591
I_3	(0.9655,1.2588,1.9676,2.3586)	1.6403
I_4	(1.1569,1.5153,2.4396,3.0471)	2.0469
I_5	(0.9795,1.2468,2.1258,2.9643)	1.8475
I_6	(0.7797,0.9755,1.6481,2.5583)	1.5173
I_7	(2.2582,3.1023,4.9744,5.4326)	3.9336
I_8	(1.5598,2.0585,3.2066,3.5950)	2.6024
I_9	(1.4480,1.8354,2.7987,3.2612)	2.3377
I_{10}	(1.0425,1.3423,2.1913,2.7971)	1.8522
I_{11}	(0.7300,0.8844,1.2988,1.7440)	1.1745
I_{12}	(2.9739,4.1258,6.6314,7.1474)	5.2064
I_{13}	(1.0987,1.3638,2.2984,3.4126)	2.0734
I_{14}	(1.8151,2.4556,4.1743,5.3643)	3.4682
I_{15}	(1.6828,2.1919,3.9102,5.7674)	3.4339
I_{16}	(0.8527,1.0340,1.6296,2.2448)	1.4547
I_{17}	(0.6425,0.7732,1.1568,1.4186)	1.0015
I_{18}	(0.5083,0.6636,1.1305,1.6895)	1.0126
I_{19}	(1.4521,1.9203,3.3417,4.6048)	2.8548

For PSS alternative s , the KLD closeness is as follows:

$$\varphi^s = \frac{KLD^{s,-}}{KLD^{s,+} + KLD^{s,-}} \quad (9)$$

where φ^s has the characteristics as follows: if $T^s = T^+$, $\varphi^s = 1$; if $T^s = T^-$, $\varphi^s = 0$; if $T^- \neq T^s \neq T^+$ and $T^s \rightarrow T^+$, $\varphi^s \rightarrow 1$.

As can be seen, KLD between evaluation object and ideal points fits well with the basic sequencing principles of TOPSIS, so KLD modified TOPSIS by replacing Euclidean distance with KLD is reasonable. We can calculate the KLD closeness between each evaluation object and ideal points successively, and obtain the final decision result of PSS alternative evaluation by sequencing PSS alternatives in the descending order.

VI. CASE STUDY

In order to promote the development of its characteristic printer and further enter the global market, improve

TABLE 5. The index values of six PSS alternatives.

	P1	P2	P3	P4	P5	P6
I_1	1.6197	1.5212	1.8913	1.4870	1.2531	3.3070
I_2	3.4591	1.1831	1.7706	1.8535	1.9996	2.8026
I_3	1.6403	3.4757	1.4176	3.1173	1.6094	3.7184
I_4	2.0469	1.3471	2.4970	2.9532	2.9424	2.1144
I_5	1.8475	2.3093	1.8365	2.3767	2.6324	3.7378
I_6	1.5173	1.4502	2.1628	1.7533	3.1572	2.6569
I_7	3.9336	2.3796	0.8371	1.6489	3.4755	2.7218
I_8	2.6024	1.5505	1.9036	1.0181	1.8755	2.3512
I_9	2.3377	2.2336	1.0621	3.7113	1.9756	3.2600
I_{10}	1.8522	0.9019	1.9088	1.6689	2.5811	2.0111
I_{11}	1.1745	1.2702	2.2529	1.4026	2.4977	2.7064
I_{12}	5.2064	1.4521	1.6907	1.4047	1.9120	1.8349
I_{13}	2.0734	2.1689	2.4123	2.7280	1.4612	0.8485
I_{14}	3.4682	1.1409	2.8014	2.5286	1.4305	3.5460
I_{15}	3.4339	2.2248	1.4496	2.6630	2.7403	2.4931
I_{16}	1.4547	1.6998	2.4597	3.0527	1.1863	2.8059
I_{17}	1.0015	1.5717	1.4177	1.4106	3.4692	2.9687
I_{18}	1.0126	2.0417	2.0600	1.8700	2.2431	2.6461
I_{19}	2.8548	2.5588	2.3335	2.6221	1.6804	3.4123

product competitiveness and achieve sustainable development, a printer company wants to evaluate several feasible PSS alternatives of its characteristic commercial printer determined in the research and development process, so as to concentrate multiple resources to ensure the effective implementation of PSS. Six PSS alternatives (P1, P2, P3, P4, P5 and P6), which are shown in Fig. 5, are generated after multi-objective configuration optimization of PSS scheme.

The stakeholder group (50 persons) consists of 10 PSS users, 10 user demand analysts, 10 PSS entrepreneurs, 10 social and environmental researchers and 10 PSS design engineers. They carry out vague assessment on the six printer PSS alternatives, and use trapezoid fuzzy numbers to express their assessment opinions on the index value. For example, to the performance of P1 on index I1, 3 stakeholders think ‘Extremely good (VC1)’, 1 stakeholder thinks ‘Strongly good (VC2)’, 5 stakeholders think ‘Obviously good (VC3)’, 17 stakeholders think ‘Slightly good (VC4)’, 1 stakeholder thinks ‘Middle (VC5)’, 9 stakeholders think ‘Slightly bad (VC6)’, 10 stakeholders think ‘Obviously bad (VC7)’, 1 stakeholder thinks ‘Strongly bad (VC8)’ and 3 stakeholders think ‘Extremely bad (VC9)’. The vague comment statistics of P1 on all 19 indexes is shown in Table 3.

TABLE 6. The positive ideal point and the negative ideal point.

	T^+	T^-
I_1	0.1623	0.0615
I_2	0.1859	0.0636
I_3	0.2575	0.0982
I_4	0.1194	0.0545
I_5	0.1726	0.0848
I_6	0.1415	0.0650
I_7	0.2969	0.0632
I_8	0.0969	0.0379
I_9	0.2309	0.0661
I_{10}	0.0929	0.0325
I_{11}	0.1210	0.0525
I_{12}	0.5017	0.1354
I_{13}	0.1228	0.0382
I_{14}	0.2363	0.0760
I_{15}	0.1479	0.0624
I_{16}	0.1544	0.0600
I_{17}	0.2277	0.0657
I_{18}	0.0946	0.0362
I_{19}	0.1288	0.0634

TABLE 7. KLD to positive and positive ideal points and KLD closeness.

	KLD		KLD closeness
	to positive ideal point	to negative ideal point	
P1	0.3723	1.0306	0.7346
P2	0.7705	0.2872	0.2715
P3	0.8276	0.2526	0.2338
P4	0.6285	0.4924	0.4393
P5	0.5648	0.5839	0.5083
P6	0.3232	0.9139	0.7387

According to Equations (1) and (2), the index value of P1 in trapezoid fuzzy number form is calculated and converted into the real number form as shown in Table 4.

Similarly, the index values of other five PSS alternatives are calculated and the index values are shown in Table 5.

Then, the weight vector is obtained by standard deviation method as follows: $\omega = [0.0491, 0.0537, 0.0693, 0.0404, 0.0462, 0.0448, 0.0755, 0.0372, 0.0622, 0.0360, 0.0447, 0.0964, 0.0450, 0.0666, 0.0431, 0.0506, 0.0656, 0.0357, 0.0377]$.

Next, we obtain the weighted index value matrix $T = [t_{s,i}]_{6 \times 19}$. Therefore, the positive ideal point and the negative ideal point are obtained as shown in Table 6.

According to Equations (7)-(9), the KLD to positive and positive ideal points and KLD closeness are shown in Table 7.

Based on KLD closeness shown in Table 6, the evaluation result of six PSS alternatives is $P6 > P1 > P5 > P4 > P2 > P3$. P6 is the best PSS alternative. Using the index value data in Table 5 and weight vector ω , the evaluation result of six PSS alternatives by traditional TOPSIS is $P6 > P1 = P4 > P5 > P2 > P3$. As can be seen, both of the evaluation results have a same ranking trend. P6 and P1 are better than

P2 and P3, while P5 and P4 are in the middle. This can prove the effectiveness of the proposed KLD modified TOPSIS. However, by traditional TOPSIS the closeness values of P1 and P4 are equal, so there is no distinction between the two. Therefore, in this case the proposed KLD modified TOPSIS can overcome the shortcoming of traditional TOPSIS.

VII. CONCLUSION

PSS is an important way for service-oriented manufacturing enterprises to meet the diversified needs of users and improve the competitiveness of enterprises. As a key stage to ensure the normal subsequent implementation, PSS evaluation decision is of great significance for the selection of PSS alternatives. In this article, a big data supported PSS evaluation decision technique is explored and the detailed steps are proposed. The case of proposed PSS evaluation decision in a printer company is given. Through analysis, the big data supported PSS evaluation decision technique explored in this article can overcome the shortcomings of the existing methods and accurately select the best PSS alternative. Therefore, it provides a practical tool for PSS evaluation decision. In future more data and cases should be used to improve the method’s feasibility and practicality. Additionally, because the indexes of PSS evaluation decision are not completely independent but related, we will use the theory of complex networks for reference to build index network model and determine the index weight in future research.

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