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Sustainability Assessment of Intelligent Manufacturing Supported by Digital Twin

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ABSTRACT As a major challenge and opportunity for traditional manufacturing, intelligent manufacturing is facing the needs of sustainable development in future. Sustainability assessment undoubtedly plays a pivotal role for future development of intelligent manufacturing. Aiming at this, the paper presents the digital twin driven information architecture of sustainability assessment oriented for dynamic evolution under the whole life cycle based on the classic digital twin mapping system. The sustainability assessment method segment of the architecture includes indicator system building, indicator value determination, indicator importance degree determination and intelligent manufacturing project assessing. A novel approach for treating the ambiguity of expert judgment in indicator value determination by introducing trapezoidal fuzzy number into analytic hierarchy process is proposed, while the complexity of the influence relationship among the indicators is processed by the integration of complex networks modeling and PROMETHEE II for the indicator importance degree determination. A two-stage evidence combination model based on evidence theory is built for intelligent manufacturing project assessing lastly. The presented digital-twin-driven information architecture and the sustainability assessment method is tested and validated on a study of sustainability assessment of 8 intelligent manufacturing projects of an air conditioning enterprise. The results of the presented method were validated by comparing them with the results of the fuzzy and rough extension of the PROMETHEE II, TOPSIS and VIKOR methods, indicator importance degree determining method by entropy and indicator value determining method by accurate expert scoring.

INDEX TERMS Digital twin, sustainability, intelligent manufacturing, fuzzy number, analytic hierarchy process, complex networks, PROMETHEE II, evidence theory.

I. INTRODUCTION

There are many definitions of sustainable development, among which the widely accepted definition is given by the World Commission on Environment and Development (WCED) in its report “our common future” published

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in 1987: development that meets the needs of contemporary people and does not harm the ability of future generations to meet their needs [1]. The report takes economic growth, social development and environmental protection as the three pillars of sustainable development. Agenda 21, adopted by the United Nations at the Rio Conference on environment and development in 1992, marks that the concept of sustainable development has been recognized by all countries in the

world [2]. As the main pillar of human civilized life style, manufacturing industry will play an important role on the road of sustainable development. The manufacturing industry not only makes the world economy get unprecedented growth and development, but also leads to the serious environment deterioration. The global environmental cost caused by production activities is as high as 4.7 trillion US dollars every year [3], [4]. The consumption of natural resources and ecological services is more than 50% of ecosystem regeneration capacity, and with the increase of population and per capita consumption level, it will face greater ecosystem pressure [5]–[7]. Hence, the sustainability of manufacturing industry is the key to achieve sustainable development.

While facing severe environmental challenges, the world undertakes the responsibility of promoting economic development and meeting the growing population and its material and cultural needs. Therefore, it is urgent to incorporate sustainable development strategy into production and manufacturing [7], [8]. In recent years, the fourth industrial revolution with intelligent manufacturing as its main feature is influencing the world economy with unprecedented depth, breadth and speed, which is likely to further deepen the development gap existing in different countries, regions or strata. At the same time, intelligent manufacturing also causes people to worry about the social impact of “replacing workers with machine”, such as unemployment, shortage of senior talents, and the coming “singularity” of environmental impact [9]–[12].

The sustainability of intelligent manufacturing is a new concept brought about by the implementation of sustainable development in the field of intelligent manufacturing [11], [12]. Faced with more and more severe environmental constraints and pressures, in order to avoid the adverse effects of intelligent manufacturing in the future and promote the development towards sustainable intelligent manufacturing, enterprises must consider the feasibility from the perspective of sustainability, and the sustainability assessment of intelligent manufacturing (SAoIM) plays an indispensable role.

At the product level, sustainability of intelligent manufacturing transcends the concept of 3R (reduce, reuse and recycle) of greenness of intelligent manufacturing to the concept of 6R (reduce, reuse, recycle, recovery, redesign and remanufacture) [8], [13], [14]. At the production level, technical improvements, such as process planning optimization and surface modification, are needed to reduce energy and resource consumption, toxic waste, occupational hazards, etc. [13], [14]. At the system level, the consideration of all aspects of the whole supply chain are needed as well as the integration the supply chain into the enterprise business model, resources and innovation strategy [8], [13]. As the market moves towards a demand driven supply chain, it is necessary to consider not only the relevance of consumers to product design and retail, but also the impact of customer choice. The sustainability of intelligent manufacturing is compared with other related features as shown in Fig. 1. It can be

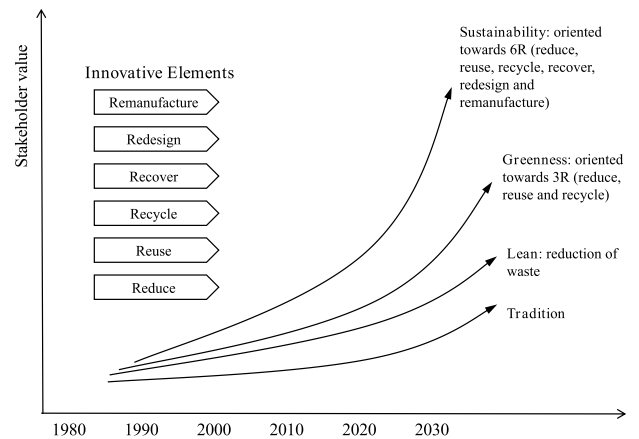


FIGURE 1. Comparison between sustainability and other related features of intelligent manufacturing in the implementation of 6R [8], [13], [14].

seen that other related features (tradition, lean and greenness) are only oriented towards part of the ‘R’ problems and the sustainability of intelligent manufacturing is oriented towards all ‘R’ problems and committed to achieve 6R.

In general, the sustainability of intelligent manufacturing is more comprehensive than other features, and its assessment needs to start from the perspective of the whole life cycle. In SAoIM, intelligent manufacturing project should be considered and assessed from the perspective of large-scale dynamic evolution system oriented to the whole life cycle. Hence, establishing information fusion architecture for the environmental and social impacts generated in the whole life cycle is very necessary.

Digital twin is considered to be the key technology in the future and has been widely concerned [15]–[18]. By digital twin, the virtual model of physical entity is created in a digital way and the behavior of physical entity is simulated by means of data. New capabilities are added or expanded for physical entities by means of virtual reality interaction feedback, data fusion analysis and decision iterative optimization. The concept of digital twin was first proposed by Professor Grieves of the University of Michigan in his product lifecycle management course. Then, the academic community has carried out relevant research on the modeling of digital twin [19], interaction and collaboration [20] and service application [21]. At present, scholars have carried out a lot of research on digital workshop/factory, and put forward many valuable theories and technologies. Sderberg *et al.* [22] applied digital twin to product production process control, thus guiding the production mode of enterprises from mass production to personalized production. Tao *et al.* [23], [24] summarized the progress in the application and theoretical research of digital twin in enterprises, put forward a five dimension structure model of digital twin and six application criteria of digital twin driving, and explored 14 types of key problems and technologies needed to be solved in the process of application conceiving and implementing driven by digital twin. In the

aspect of digital twin framework research, Zhang *et al.* [25] proposed the optimal state control (OsC) method to help synchronized production operation system (SPOS) keep in an optimal state when uncertainties affect the system and designed a digital twin-based control framework (DTCF) for getting the full element information needed for decision making. Li *et al.* [26] proposed a digital twin-driven framework to enhance the optimization of product-service system (PSS) scheme selection. The framework is divided into a digital twin layer, an information layer, and an approach layer.

Digital twin can build a real-time complete model of the physical layer in the virtual layer, which provides a suitable information framework. Based on the prior researches [25], [26], the benchmarks of digital twin framework are abstracted as follows. The framework can mainly be divided into two layers: physical object layer and virtual decision/control layer.

- Physical object layer. It is an objective entity set. It receives decision-making task instructions issued by various information systems. The information can be collecting, sensing, processing and transmitted to provide basic data support for virtual control/control layer. There are two sub-layers in physical object layer: (1) Resource sets layer: various resource entities; (2) Information processing layer: making the resources intelligent, integrating and pre-processing the information.
- Virtual decision/control layer. All decisions and control can be complete in this layer. The control instructions are fed back to the physical layer through cyber-physical system (CPS). Based on the multi-dimensional or multi-granularity heterogeneous static model and real-time data collected by the physical object layer, the physical execution units of the physical layer are mapped to the virtual layer by the twin modeling technology. According to the relationship corresponding to the physical layer, a virtual system is formed in the virtual layer, and the process of the physical layer is systematically and accurately mapped. The decision/control mechanism should be imported to this layer at the same time, which makes the dynamical decision/control possible.

Aiming at the problem that production execution information and machine tool operation information have different sources, and the integration of the two types of information is difficult, Coronado *et al.* [25] proposed a new manufacturing execution system, which uses data to build a digital twin workshop for production control and optimization. Banerjee *et al.* [26] combined knowledge learning with digital twin, and proposed a method to extract and infer knowledge from large-scale production line data and improve manufacturing process management through reasoning ability. These studies provide theoretical and methodological references for the further application of digital twins in the future.

Although the digital twin technology has formed an effective management mode and technical framework for the digital modeling and interactive control of physical objects, its application scope is mostly limited to independent objects and the researches on overall associated twinning and collaborative decision-making of large-scale dynamic evolution system oriented to the whole life cycle are few. In SAoIM, intelligent manufacturing project involves many related environmental and social factors in the dynamic evolution of its whole life cycle. Therefore, how to extend the digital twin model to the whole life cycle system of intelligent manufacturing project dynamic evolution and realize the assessment of many related factors is an urgent problem to be solved. Oriented for dynamic evolution under the whole life cycle of intelligent manufacturing, building digital-twin-driven information architecture of sustainability assessment based on the classic digital twin mapping system is a feasible solution.

Sustainability assessment method for intelligent manufacturing project is the core of the digital-twin-driven information architecture of sustainability assessment. Sustainability assessment problem can be considered as a complex multi-criteria decision-making (MCDM) problem, which concerns many factors ranging from environmental effects to social effects. To the best of our knowledge, there is no systematic research for the sustainability assessment of intelligent manufacturing project. However, there are enough similar MCDM research which can serve as reference and guidance for this work, for example, an extended Complex Proportional Assessment (COPRAS) model for web-based hotel evaluation and selection [27], an extension of the Combinative Distance-Based Assessment (CODAS) approach using interval-valued intuitionistic fuzzy set for sustainable material selection in construction projects [28], a rough strength relational Decision Making Trial and Evaluation Laboratory (DEMATEL) model for analyzing the key success factors of hospital service quality [29], a rough analytic hierarchy process (AHP) based multi-attributive border approximation area comparison approach for evaluation and selection of medical tourism sites [30], a modification approach of the Best-Worst Method (BWM) and Multi-Attributive Border Approximation Area Comparison (MABAC) method: based on interval-valued fuzzy-rough numbers [31] and a hybrid group MCDM model based on DEMATEL, Analytic Network Process (ANP) and Multi Attributive Ideal-Real Comparative Analysis (MAIRCA) [32]. Wu *et al.* [33] proposed an integrated approach of the interval type-2 fuzzy best-worst and extended VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) for green supplier selection. Based on improved supplementary regulation and operational laws Xiao *et al.* [34] constructed a novel hesitant fuzzy linguistic multi-attribute group decision making method. Li *et al.* [35] built a conjunctive MCDM approach for cloud service supplier selection based on neural network, fuzzy AHP, Criteria Importance through Inter-criteria Correlation (CRITIC) and

Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS).

Dealing with crisp data or fuzzy information, the above-mentioned papers mainly studied one or several stages of the MCDM process and could not cover the whole process generally including indicator value solving, indicator weight determining and object evaluation. Therefore, there is lack of a systematic method or model.

Thus, this research paper seeks answers to the following questions:

(1) How to build digital-twin-driven information architecture of sustainability assessment of intelligent manufacturing project?

(2) How to design a systematic method or model for sustainability assessment of intelligent manufacturing project cover the whole MCDM process?

To fill up this gap, this paper attempts to develop a digital-twin-driven information architecture based on the classic digital twin mapping system is a feasible solution for sustainability assessment of intelligent manufacturing project. This architecture orients for dynamic evolution under the whole life cycle and extends the classical digital twin mapping system to a digital twin control system which meets the requirements of dynamic evaluation of all factors. Furthermore, a systematic sustainability assessment method for intelligent manufacturing project is designed based on the fuzzy perception of experts about indicator value and indicator importance degree. This systematic method includes three parts: (1) Indicator value solving. Fuzzy number can better reflect the uncertainty of expert's judgment compared with accurate number [35]–[38]. Using fuzzy number to express expert's judgment is more reasonable when evaluating the performance of intelligent manufacturing project alternatives. (2) Indicator importance degree (weight) determination. The determination of indicator importance degree is similar to the evaluation of node importance in complex networks. In the complex networks of indicators, the nodes in the network represent the indicators, and the connection between the nodes reflects the relationship between the indicators. At present there are many researches and applications on node importance evaluation in complex networks [39]–[42]. This paper considers the multi-type centrality attribute of nodes and introduces preference ranking organization methods for enrichment evaluations II (PROMETHEE II) [43]–[45] to determine the indicator importance degree. Considering the relationship among multiple indicators, the network attributes are used to analyze the interaction among indicators, which is more objective. PROMETHEE II considers the preference of decision makers in the evaluation process. This combination of subjective and objective can make up for the shortcomings of previous researches. (3) Object evaluation. Dempster Shafer theory (D-S theory) [46]–[48] can directly express uncertainty, which provides an effective method for the expression and synthesis of uncertain information. This paper creatively applies D-S theory to assessment problem. Based on D-S theory, a discrimination framework for

sustainability assessment of intelligent manufacturing project can be established by treating indicator information as evidence. Through evidence combination the sustainability assessment of intelligent manufacturing project is achieved.

This paper is organized into six sections. After the introductory section, the second section presents the digital-twin-driven information architecture of SAoIM. The sustainability assessment method is presented under the expert assessment framework in the third section. Then it is tested and verified in the fourth by means of a case study in which the sustainability of eight intelligent manufacturing project alternatives in an air conditioning enterprise are assessed. The discussions of the results and validation of the proposed method are given in the fifth section. Lastly, the sixth section presents concluding considerations with a special emphasis on directions for further research.

II. DIGITAL-TWIN-DRIVEN INFORMATION ARCHITECTURE

In order to eliminate or reduce the influence of static assessment and one-sided assessment, the sustainability assessment of intelligent manufacturing requires comprehensively considering the related environmental and social factors that evolve dynamically with the whole life cycle, so as to realize effective assessment.

By extending the classical digital twin mapping system [22]–[26] to a digital twin control system which meets the requirements of dynamic evaluation of all factors, we build the digital-twin-driven information architecture of sustainability assessment oriented for dynamic evolution under the whole life cycle as shown in Fig. 2. Based on dynamic state perception of all elements, the virtual mapping technology and intelligent assessment method are adopted to provide basic information and service support for the sustainability assessment of intelligent manufacturing. The information architecture includes three layers: physical object layer, virtual model layer and application layer.

The details of the three layers are as follows.

A. PHYSICAL OBJECT LAYER

Mainly through radio frequency identification (RFID), quick response (QR) code tags, sensors, wireless sensor network (WSN), global positioning system (GPS) and other intelligent sensing and positioning technologies, the real-time dynamic state perception and monitoring of the multi-source heterogeneous information related to the environmental and social effects in the whole life cycle of intelligent manufacturing is carried out. Based on this, the intelligent perception and interconnection, real-time interaction and control, and intelligent cooperation and integration of the dynamic evolution process of intelligent manufacturing project are realized.

B. VIRTUAL MODEL LAYER

Based on the multi-dimensional and multi-granularity heterogeneous static model data and dynamic running data collected by the physical object layer in the actual evolution

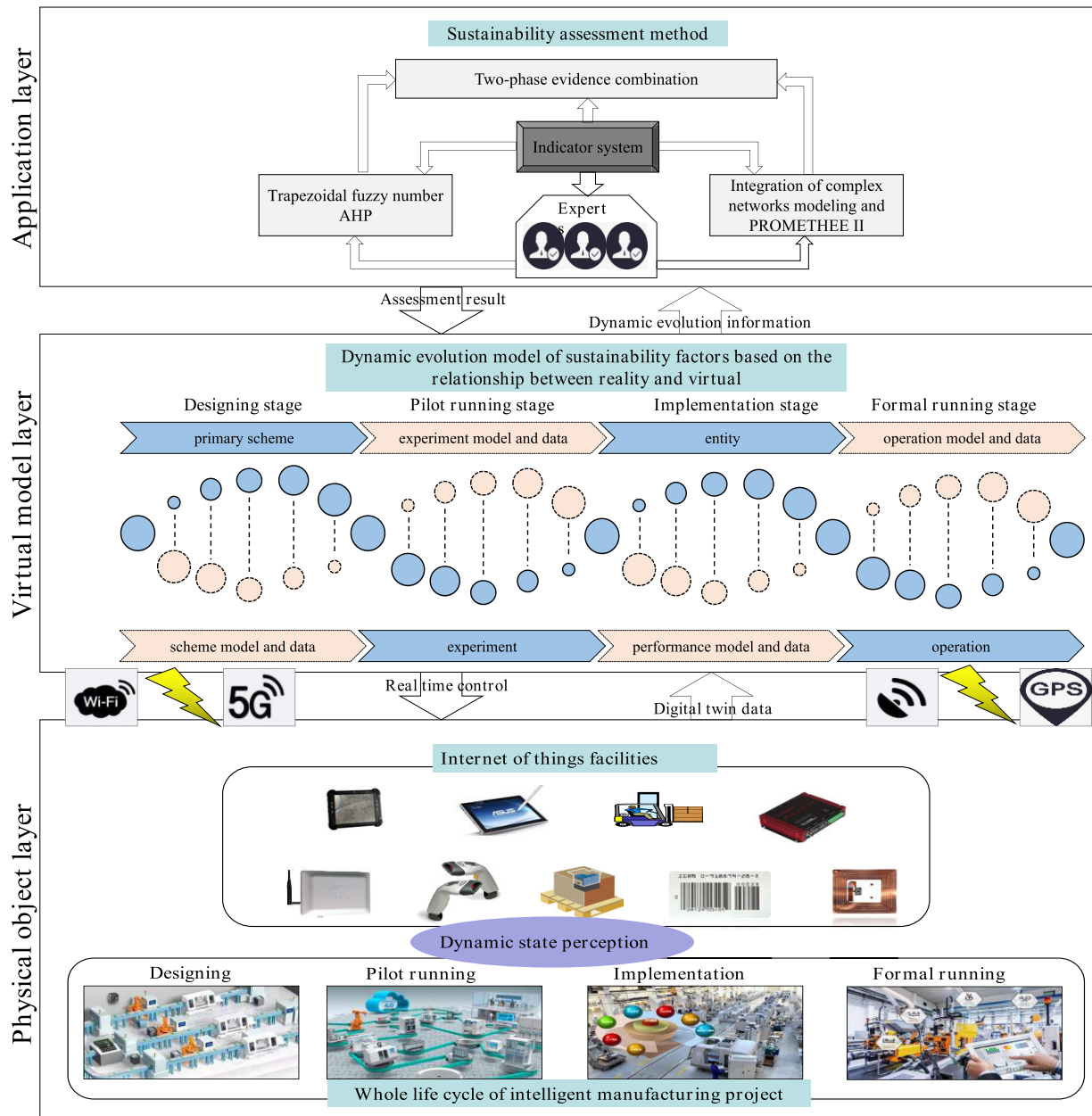


FIGURE 2. Digital-twin-driven information architecture of SAoIM oriented for dynamic evolution under the whole life cycle.

process of intelligent manufacturing project, the physical layer is mapped into a virtual execution unit which can reflect the real-time running state through digital twin modeling technology in the virtual layer and a virtual environment and social influence factor evolution model is formed in the virtual layer according to the dynamic evolution of intelligent manufacturing projects in the physical layer. Thus, the dynamic evolution of intelligent manufacturing project in physical layer is systematically precisely mapped and dynamically feedback-controlled.

C. APPLICATION LAYER

Based on the accurate identification and monitoring of the dynamic evolution of environmental and social impacts in

the whole life cycle of intelligent manufacturing, the sustainability of intelligent manufacturing is assessed under the expert assessment framework based on a novel MCDM method. In the proposed MCDM method, trapezoidal fuzzy number (TFN) is introduced into AHP for the determination of indicator value, which is abbreviated as TFN-AHP; the indicator importance degree is determined by the integration of complex networks modeling and PROMETHEE II; the sustainability of intelligent manufacturing projects are assessed by two-stage evidence combination based on evidence theory finally. In addition, the sustainability assessment of intelligent manufacturing is encapsulated in the customized interactive intelligent application system of the physical layer in the form of application service, so as to realize the interaction

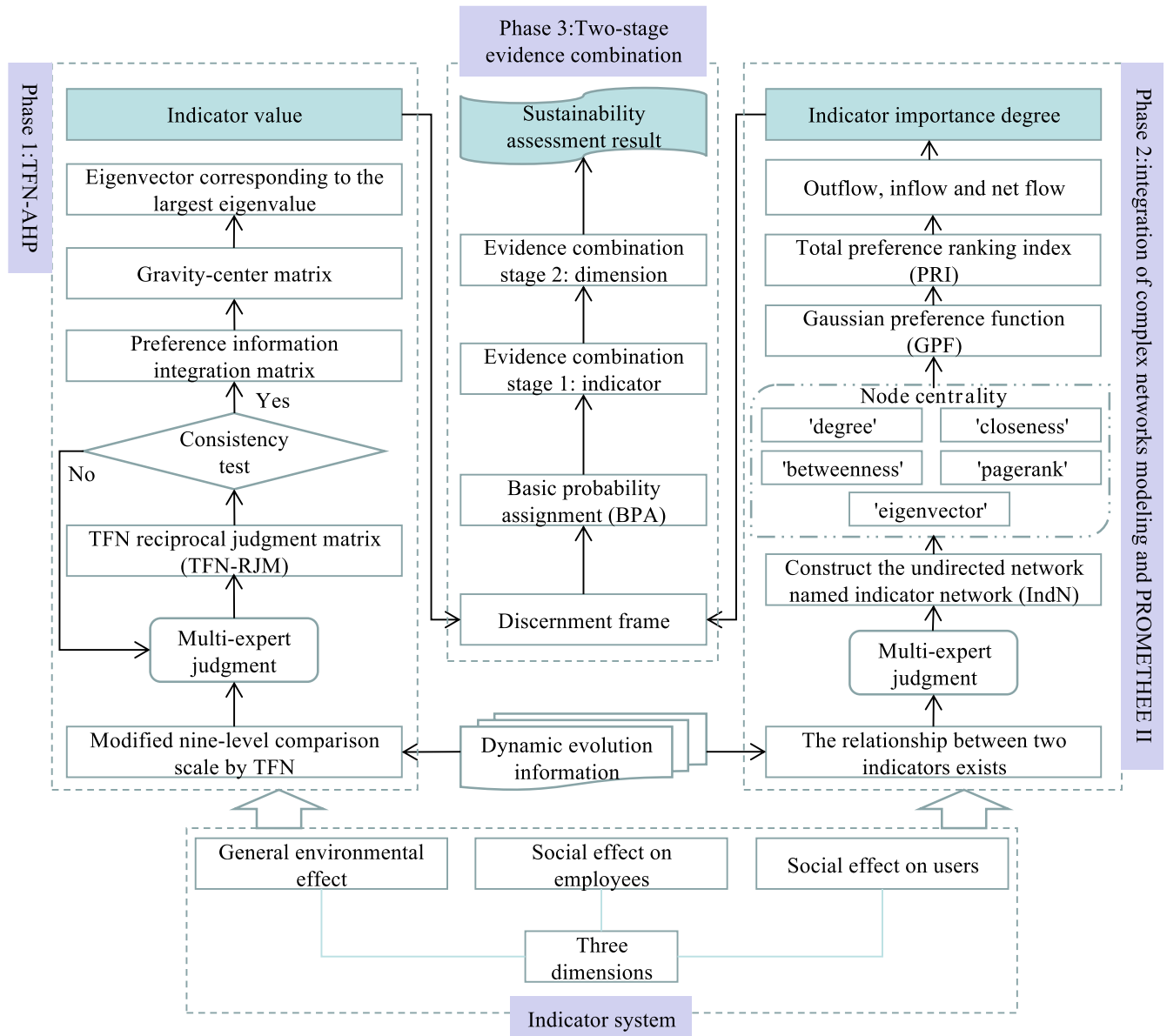


FIGURE 3. The multi-phase model for sustainability assessment.

and feedback of information decision-making and physical execution.

III. SUSTAINABILITY ASSESSMENT METHOD

By introducing the multi-phase model as shown in Fig. 3, this paper presents a sustainability assessment method under the digital-twin-driven information architecture of SAoIM shown in Section II. The indicator system of SAoIM including three dimensions and nine indicators is built firstly.

TFN is used to deal with uncertainty of expert judgment in the group decision making process, while AHP is used to integrate the judgments of multiple experts. Phase 1 includes the expert judgment of assessment indicator value by applying the TFN-AHP model, which results in the creation of input data required for the two-stage evidence combination

model (Phase 3). In phase 2, whether the influence relationship among the indicators exists or not is evaluated by multiple experts and the evaluation result is used to build the indicator network, and then the indicator importance degree is determined by PROMETHEE II based on multiple network properties. The output data of phase 2 is the indicator importance degree which is the input data of phase 3. The discernment frame for SAoIM based on evidence theory is defined in phase 3. According to the two-tier indicator system of SAoIM, the sustainability of intelligent manufacturing projects is assessed by two-stage evidence combination taking indicator value (phase 1) and indicator importance degree (phase 2) as input data.

The following four sub-sections deal with the algorithms for the multi-phase model.

A. INDICATOR SYSTEM

The influence factors of SAoIM mainly include general environmental effect, social effect on employees and social effect on users based on the summary of the existing research. Different from the energy consumption and water consumption, environmental effect can directly, comprehensively and objectively reflect the actual effect on the ecological environment and human health. In the current critical period of manufacturing transformation and upgrading, the analysis of employee effect has more important significance and different focus. In these studies, social effect assessment is carried out by selecting social effect indexes independently and setting scoring standards. Therefore, this paper mainly combines the actual situation of intelligent manufacturing and related research to build the indicator system of SAoIM, which is a concise two-tier architecture including three dimensions and nine indicators as shown in Fig. 4.

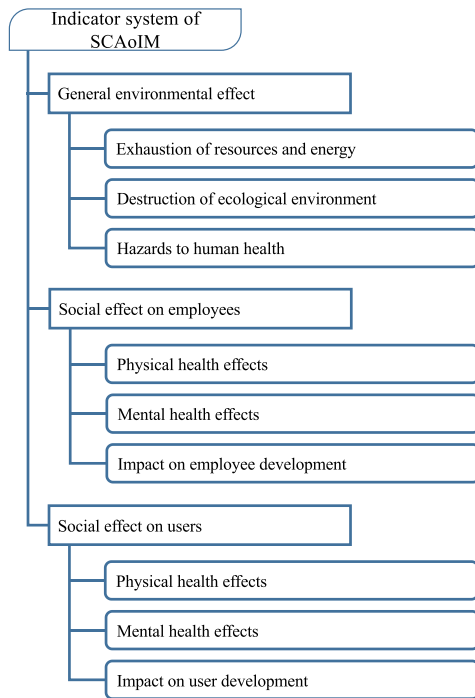


FIGURE 4. The indicator system of SAoIM.

From the perspective of dimension, the indicator system of SAoIM includes three dimensions, which are general environmental effect (dimension D1), social effect on employees (dimension D2) and social effect on users (dimension D3). In each dimension there are several corresponding indicators. Based on the indicator system shown in Fig. 3, the methodology of SAoIM supported by digital twin is presented with three steps as follows.

B. TFN-AHP

Based on the digital-twin-driven information architecture (Fig. 2), in the virtual model layer the dynamic evolution of intelligent manufacturing project in physical layer is

systematically precisely mapped and dynamically feedback-controlled. Experts can comprehensively master the complete information in the digital-twin model in the virtual model layer and make a relatively objective judgment based on their experience and wisdom.

The group experience and wisdom of expert can be fully used by judgment opinion integration of multiple experts. Therefore we adopt this train of thought in the indicator value determination of SAoIM. However, when an expert evaluates the performance of two intelligent manufacturing projects on an indicator, his judgment opinion depends on the personal experience and wisdom of him, so it is unreasonable to express the judgment opinion with accurate numbers. Compared with accurate number, fuzzy number can reflect the internal uncertainty of expert's judgment opinion [27]–[31]. The commonly used fuzzy numbers include triangular fuzzy numbers and trapezoidal fuzzy numbers. As for membership function, trapezoidal fuzzy number is more complex than triangular fuzzy number. Compared to triangular fuzzy number, trapezoidal fuzzy number can better express and describe the vagueness and uncertainty in nature of expert's judgment. Therefore, trapezoidal fuzzy number is integrated into the MCDM process.

Some definitions about fuzzy number are as follows.

Definition 1 (Trapezoid Fuzzy Number (TFN) [37], [38]): If four real numbers satisfy $a \leq b \leq c \leq d$, $\varepsilon = (a, b, c, d)$ can be defined as a TFN. Here, a is the upper bound of ε while b is the lower bound of ε . Especially, if $b = c$, ε is a triangular fuzzy number; while if $a = b = c = d$, ε is a real number.

Definition 2 (Membership Function (MF) [37], [38]): The MF of TFN $\varepsilon = (a, b, c, d)$ is defined as $f(x) : R \rightarrow [0, 1]$. When $a \leq x \leq b$, $f(x) = (x - a)/(b - a)$ is named as left MF $f^L(x)$, which is a strictly increasing function; when $b \leq x \leq c$, $f(x) = 1$; when $c \leq x \leq d$, $f(x) = (d - x)/(d - c)$ is named as right MF $f^R(x)$, which is a strictly reducing function; else, $f(x) = 0$. The inverse functions of $f^L(x)$ and $f^R(x)$ are as follows.

$$\begin{aligned} g^L(y) &= a + (b - a)y \\ g^R(y) &= d + (c - d)y \end{aligned} \quad (1)$$

where $0 \leq y \leq 1$.

Definition 3 (Desired Value (DV) [37], [38]): For TFN ε its left DV is $D^L(\varepsilon) = \int_0^1 g^L(y)dy = (a + b)/2$, while its right DV is $D^R(\varepsilon) = \int_0^1 g^R(y)dy = (c + d)/2$. The DV of ε is defined as follows.

$$D(\varepsilon) = \alpha D^L(\varepsilon) + \beta D^R(\varepsilon) \quad (2)$$

where α and β are the optimistic coefficient and pessimism coefficient respectively, $\alpha \geq 0$, $\beta \geq 0$, $\alpha + \beta = 1$.

Definition 4 (Gravity Center [37], [38]): For TFN ε its gravity center is defined as follows.

$$G(\varepsilon) = \frac{(c^2 + d^2 + cd)^2 - (a^2 + b^2 + ab)^2}{3(c + d - a - b)} \quad (3)$$

For any two TFNs $\varepsilon_1 = (a_1, b_1, c_1, d_1)$ and $\varepsilon_2 = (a_2, b_2, c_2, d_2)$ which satisfy $\varepsilon_1 > 0$, $\varepsilon_2 > 0$ and $\chi > 0$,

the arithmetic operation rules are as follows.

$$\varepsilon_1 + \varepsilon_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2) \quad (4)$$

$$\varepsilon_1 \varepsilon_2 = (a_1 a_2, b_1 b_2, c_1 c_2, d_1 d_2) \quad (5)$$

$$\chi \varepsilon_1 = (\chi a_1, \chi b_1, \chi c_1, \chi d_1) \quad (6)$$

$$(\varepsilon_1)^{-1} = (1/d_1, 1/c_1, 1/b_1, 1/a_1) \quad (7)$$

$$\varepsilon_1 / \varepsilon_2 = (a_1/d_2, b_1/c_2, c_1/b_2, d_1/a_2) \quad (8)$$

According to the MF of TFN, natural numbers (1 to 9) can be transformed into corresponding TFNs as shown in Table 1.

TABLE 1. The TFNs corresponding to natural numbers.

Natural number	TFN
1	(1,1,3/2,2)
2	(1,3/2,5/2,3)
3	(2,5/2,7/2,4)
4	(3,7/2,9/2,5)
5	(4,9/2,11/2,6)
6	(5,11/2,13/2,7)
7	(6,13/2,15/2,8)
8	(7,15/2,17/2,9)
9	(8,17/2,9,9)

In the traditional comparison judgment matrix, the value of each element generally adopts the nine-level comparison scale method. Because the judgment thinking of experts is subjective and uncertain, it is unreasonable to use the accurate nine-level comparison scale. In view of this defect of traditional nine-level comparison scale method, we modify it by replacing the accurate scale with TFN. According to the arithmetic operation rules of TFN, the modified nine-level comparison scale method can be shown in Table 2.

According the above definitions about TFN and the transformations from traditional nine-level comparison scale to modified nine-level comparison scale by TFN, the TFN-AHP approach for indicator value determination of SAoIM is presented as follow.

There are m alternatives of intelligent manufacturing project and s experts to evaluate the sustainability of them on each indicator shown in Fig. 3. It is assumed that all experts are equal.

Taking indicator I_j ($1 \leq j \leq n$) as an instance, the solution process of indicator values is illustrated. On indicator I_j , s experts separately carry out the pairwise comparison of the capability of m alternatives based on the modified nine-level comparison scale method (Table 2). The TFN reciprocal judgment matrix (TFN-RJM) is given by each of s experts, respectively. To expert p ($1 \leq p \leq s$), his TFN-RJM is as follows.

$$E^{(j,p)} = [\varepsilon_{i,k}^{(j,p)}]_{n \times n} \quad (9)$$

where $\varepsilon_{i,k}^{(j,p)} = (a_{i,k}^{(j,p)}, b_{i,k}^{(j,p)}, c_{i,k}^{(j,p)}, d_{i,k}^{(j,p)})$ is a TFN and stands for the capability of alternative i relative to alternative k on

indicator I_j judged by expert p , $1 \leq i \leq m$, $1 \leq k \leq m$ and $\varepsilon_{k,i}^{(j,p)} = 1/\varepsilon_{i,k}^{(j,p)}$.

Consistency test will be carried out for TFN-RJM $E^{(j,p)}$. Firstly, $E^{(j,p)}$ is mapped into a real number matrix $DV^{(j,p)} = [DV(\varepsilon_{i,k}^{(j,p)})]_{n \times n}$ where $DV(\varepsilon_{i,k}^{(j,p)})$ is the DV of $\varepsilon_{i,k}^{(j,p)}$ just as follows.

$$DV(\varepsilon_{i,k}^{(j,p)}) = \alpha D^L(\varepsilon_{i,k}^{(j,p)}) + \beta D^R(\varepsilon_{i,k}^{(j,p)}) \quad (10)$$

Here, let $\alpha = \beta = 0.5$, which means staying neutral. The DV of $\varepsilon_{i,k}^{(j,p)}$ is obtained as follows.

$$DV(\varepsilon_{i,k}^{(j,p)}) = \frac{a_{i,k}^{(j,p)} + b_{i,k}^{(j,p)} + c_{i,k}^{(j,p)} + d_{i,k}^{(j,p)}}{4} \quad (11)$$

Then the consistency ratio of $DV^{(j,p)}$ is obtained as follows.

$$CR(DV^{(j,p)}) = \frac{CI(DV^{(j,p)})}{RI(DV^{(j,p)})} \quad (12)$$

where $CI(DV^{(j,p)}) = (\lambda_{\max} - n)/(n - 1)$ is the consistency index, λ_{\max} is the largest eigenvalue of $DV^{(j,p)}$; while $RI(DV^{(j,p)})$ is the average random consistency index related to order n .

When $CR(DV^{(j,p)}) \leq 0.1$, TFN-RJM $E^{(j,p)}$ pass the consistency test and could be used for decision-making. Else, expert p should adjust his judgment matrix.

The preference information of each expert is integrated into a preference information integration matrix as follows.

$$E^{(j)} = [\varepsilon_{i,k}^{(j)}]_{n \times n} \quad (13)$$

where

$$\begin{aligned} \varepsilon_{i,k}^{(j)} &= (a_{i,k}^{(j)}, b_{i,k}^{(j)}, c_{i,k}^{(j)}, d_{i,k}^{(j)}), \quad a_{i,k}^{(j)} = \sum_{p=1}^s a_{i,k}^{(j,p)} / s, \\ b_{i,k}^{(j)} &= \sum_{p=1}^s b_{i,k}^{(j,p)} / s, \quad c_{i,k}^{(j)} = \sum_{p=1}^s c_{i,k}^{(j,p)} / s, \\ d_{i,k}^{(j)} &= \sum_{p=1}^s d_{i,k}^{(j,p)} / s. \end{aligned}$$

By the conversion based on gravity-center formula of TFN (Formula (3)), $E^{(j)}$ can be converted into gravity-center matrix as follows.

$$\hat{E}^{(j)} = [\hat{\varepsilon}_{i,k}^{(j)}]_{n \times n} \quad (14)$$

where $\hat{\varepsilon}_{i,k}^{(j)}$ is the gravity center of $\varepsilon_{i,k}^{(j)}$.

To $\hat{E}^{(j)}$, the eigenvector corresponding to its largest eigenvalue is obtained as follows.

$$\delta(\hat{E}^{(j)}) = [\delta_1(\hat{E}^{(j)}), \delta_2(\hat{E}^{(j)}), \dots, \delta_n(\hat{E}^{(j)})]^T \quad (15)$$

The indicator value of alternative i on indicator I_j is obtained as follows.

$$x_{i,j} = \frac{\delta_i(\hat{E}^{(j)})}{\sum_{i=1}^m \delta_i(\hat{E}^{(j)})} \quad (16)$$

The indicator values of m alternatives on other indicators can be obtained by same way. At last, we get the indicator value matrix as $X = [x_{i,j}]_{m \times n}$.

TABLE 2. The transformations from traditional nine-level comparison scale to modified nine-level comparison scale by TFN.

Comparison relationship of two objects	Traditional scale	Modified scale	Corresponding TFN
Extremely inferior	1	1/9	(1/9,1/9,3/17,1/4)
Strong inferior	2	2/8	(1/9,3/17,1/3,3/7)
Obviously inferior	3	3/7	(1/4,1/3,7/13,2/3)
Slightly inferior	4	4/6	(3/7,7/13,9/11,1)
Identical	5	5/5	(1,1,1,1)
Slightly superior	6	6/4	(1,11/9,13/7,7/3)
Obviously superior	7	7/3	(3/2,13/7,3,4)
Strongly superior	8	8/2	(7/3,3,17/3,9)
Extremely superior	9	9/1	(4,17/3,9,9)

C. INTEGRATION OF COMPLEX NETWORKS MODELING AND PROMETHEE II

There's a relationship between the indicators of SAoIM. For example, destruction of ecological environment (indicator I_2 in dimension D1) affects physical health effects (indicator I_4 in dimension D2) and physical health effects (indicator I_7 in dimension D3), so there is a relationship between I_2 and I_4 , while there is also a relationship between I_2 and I_7 . In view of this, by treating indicators as nodes a network of the indicators of SAoIM can be constructed based on the relationship between them. Then the indicator importance in the architecture (Fig. 3) is transformed into the node importance in the network. Whether the relationship between two indicators exists or not is evaluated by multiple experts, and an undirected network named indicator network (IndN) is constructed based on the evaluation result.

In the constructed IndN, the node set is defined as $\{I_1, I_2, \dots, I_n\}$ where node I_j stands for indicator I_j . According to the complex networks theory [39]–[42], centrality is used to measure node importance in a network. Generally, centrality can be distributed into five types as follows.

1) 'DEGREE' (cen^1) [39]–[42]

It means the number of edges connecting to each node. The 'degree' centrality type is based on the number of edges connecting to each node, and a self-loop counts as two edges connecting to the node. If there are θ_j nodes that directly connect to node I_j in IndN, the degree of node I_j is:

$$cen_j^1 = \theta_j \quad (17)$$

2) 'CLOSENESS' (cen^2) [39]–[42]

The 'closeness' centrality type uses the inverse sum of the distance from a node to all other nodes in the network. If not all nodes are reachable, then the centrality of node I_j is:

$$cen_j^2 = \left(\frac{\varsigma_j}{n-1}\right)^2 \frac{1}{\xi_j} \quad (18)$$

where ς_j is the number of reachable nodes from node I_j (not counting I_j) and ξ_j is the sum of distances from node I_j to all

reachable nodes. If no nodes are reachable from node I_j , then cen_j^2 is zero.

3) 'BETWEENNESS' (cen^3) [39]–[42]

The 'betweenness' centrality type measures how often each node appears on a shortest path between two nodes in the network. Since there can be several shortest paths between two nodes s and t node I_u and I_t , the centrality of node I_j is:

$$cen_j^3 = \sum_{u,t \neq j} \frac{\vartheta_{ut}^j}{\vartheta_{ut}} \quad (19)$$

where ϑ_{ut}^j is the number of shortest paths from I_u to I_t that pass through node I_j , and ϑ_{ut} is the total number of shortest paths from I_u to I_t . If the network is undirected, then the paths from I_u to I_t and from I_t to I_u count only as one path (divide the formula by two).

4) 'PAGERANK' (cen^4) [39]–[42]

The 'pagerank' centrality type results from a random walk of the network. At each node in the network, the next node is chosen with a certain probability from the set of successors of the current node (neighbors for the undirected case). Otherwise, or when a node has no successors, the next node is chosen from all nodes. The 'pagerank' centrality score (pag_j) is the average time spent at each node during the random walk. If a node has a self-loop, then there is a chance that the algorithm traverses it. Therefore self-loops increase the 'pagerank' centrality score of the node they attach to. In networks with multiple edges between the same two nodes, nodes with multiple edges are more likely to be chosen.

5) 'EIGENVECTOR' (cen^5) [39]–[42]

The 'eigenvector' centrality type uses the eigenvector corresponding to the largest eigenvalue of the network adjacency matrix. The scores are normalized such that the sum of all centrality scores is one. The 'eigenvector' centrality score (eig_j) of disconnected nodes is $1/n$.

The properties ('degree', 'closeness', 'betweenness', 'pagerank' and 'eigenvector') of a node describe its importance in the network from different perspectives according to complex networks theory.

The traditional methods (such as AHP [30] and DEMATEL [29]) have decision compensation in the evaluation, that is, the high value of one attribute can make up for the low value of other attributes. The core idea of PROMETHEE II is outranking method [31], [32], [47], [48]. The preference function is used to compare two objects one by one, and the preference order of all objects is finally determined, thus avoiding the influence of compensation on the decision results. In addition, PROMETHEE II does not need nondimensionalized and normalized processing of the attribute value, which reasonably avoids the information deviation in data processing. This paper adopts PROMETHEE II to determine the importance degrees of all nodes in IndN, which indicate the importance degrees of the indicators shown in Fig. 3.

Here, Gaussian preference function (GPF) is chosen because of its nonlinear feature, which is more reasonable to the realistic decision-making situation of this study.

For the ‘degree’ centrality type, the GPF of node I_j relative to node I_u is obtained as follows.

$$GPF_{j,u}^1 = \begin{cases} 0, & cen_j^1 - cen_u^1 \leq 0 \\ 1 - e^{-\frac{(cen_j^1 - cen_u^1)^2}{2\eta^2}}, & cen_j^1 - cen_u^1 > 0 \end{cases} \quad (20)$$

where η is a constant that generally is 0.2.

Similarly, for the ‘closeness’, ‘betweenness’, ‘pagerank’ and ‘eigenvector’ centrality type, the GPFs $GPF_{j,u}^2$, $GPF_{j,u}^3$, $GPF_{j,u}^4$ and $GPF_{j,u}^5$ of node I_j relative to index node I_u can be obtained by same way.

The total preference ranking index (PRI) [43]–[45] of node I_j relative to node I_u , which indicates the importance degree of node I_j over node I_u considering all five centrality types is obtained as follows.

$$PRI_{j,u} = \sum_{q=1}^5 \rho_q GPF_{j,u}^q \quad (21)$$

where $\rho_q (1 \leq q \leq 5)$ is a coefficient, $\rho_q \geq 0$ and $\sum_{q=1}^5 \rho_q = 1$.

The outflow of node I_j indicates the importance degree of node I_j over all other indicators, while the inflow of node I_j indicates the importance degree of all other indicators over node I_j . Then the net flow of node I_j reflects the whole importance degree of node I_j . The outflow, inflow and net flow of node I_j are obtained as follows.

$$Out_j = \sum_{u=1}^n PRI_{j,u} \quad (22)$$

$$In_j = \sum_{u=1}^n PRI_{u,j} \quad (23)$$

$$Net_j = Out_j - In_j \quad (24)$$

If a node has a greater net flow, it means this node has a greater importance degree in IndN. However, the net flow of some nodes may be negative, and normalizing the net flows

of all nodes is necessary. After normalizing, the importance degree of node I_j is obtained as follows.

$$w_j = \frac{norNet_j}{\sum_{j=1}^n norNet_j} \quad (25)$$

where $norNet_j$ is the normalized form of Net_j . Because node I_j in IndN indicates indicator I_j in the indicator system shown in Fig. 3, the importance degree vector of all indicators is obtained as $w = [w_1, w_2, \dots, w_n]^T$.

D. TWO-STAGE EVIDENCE COMBINATION

According to evidence theory [46]–[48], m alternatives of intelligent manufacturing project in the sustainability assessment problem are treated as the elements in the discernment frame. Therefore, the discernment frame is defined as follows.

$$\Phi = \{\varphi_1, \varphi_2, \dots, \varphi_m\} \quad (26)$$

where φ_i stands for alternative i .

The most basic information carrier in evidence theory is called basic probability assignment (BPA) [46]–[48]. In the discernment frame, BPA is a function named as mass function, which satisfies $mass(\emptyset) = 0$ and $\sum_{\varphi \subseteq \Phi} mass(\varphi) = 1$. Here, $mass(\varphi)$ means the supportiveness for φ of the evidence. When $mass(\varphi) > 0$, φ is a focal element. To $\varphi \subseteq \Phi$, the combination rule of l mass functions is as follows.

$$mass_{1 \odot 2 \odot \dots \odot l}(\varphi) = \frac{1}{K} \sum_{\varphi^{(1)} \cap \varphi^{(2)} \cap \dots \cap \varphi^{(l)} = \varphi} mass_1(\varphi^{(1)}) \times mass_2(\varphi^{(2)}) \dots mass_l(\varphi^{(l)}) \quad (27)$$

where “ \odot ” is the symbol of combination of multiple mass functions and $\varphi^{(1)}, \varphi^{(2)}, \dots, \varphi^{(l)} \subseteq \Phi$.

Here, K is the normalization constant as follows.

$$K = \sum_{\varphi^{(1)} \cap \varphi^{(2)} \cap \dots \cap \varphi^{(l)} \neq \emptyset} mass_1(\varphi^{(1)}) mass_2(\varphi^{(2)}) \dots mass_l(\varphi^{(l)}) \quad (28)$$

Intelligent manufacturing project assessing by evidence theory is a two-stage evidence combination process as shown in Fig. 5. Its details are as follows.

Based on the indicator value and indicator importance degree, the mass function values of all focal elements (contain m alternatives and special focal element Φ) on indicator I_j are standardized. Then the standardized mass functions of all focal elements on indicator I_j are obtained as follows.

$$w - mass_j(\varphi_i) = \begin{cases} w_j \frac{x_{i,j}}{\sum_{i=1}^m x_{i,j}}, & \varphi_i \neq \Phi \\ 1 - w_j, & \varphi_i = \Phi \end{cases} \quad (29)$$

According to the indicator system shown in Fig. 4, for the indicators in dimension D1, the standardized mass functions of m alternatives are treated as evidence and combined based on the combination rule shown in Formula (27), thus the mass

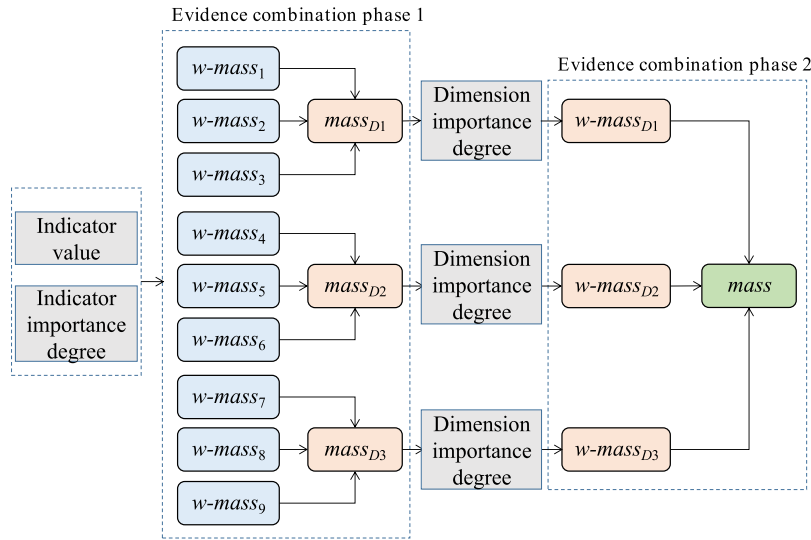


FIGURE 5. The two-stage evidence combination.

function $mass_{D1}$ of all focal elements on dimension D1 can be obtained as follows.

$$mass_{D1}(\varphi) = \frac{1}{K} \sum_{\varphi^{(1)} \cap \varphi^{(2)} \cap \varphi^{(3)} = \varphi} w - mass_1(\varphi^{(1)}) \cdot w - mass_2(\varphi^{(2)}) \cdot w - mass_3(\varphi^{(3)}) \quad (30)$$

By the same way, the mass functions $mass_{D2}$ and $mass_{D3}$ of all focal elements on dimension D1 and dimension D2 can also be obtained.

Subsequently, the standardization of mass function $mass_{D1}$ of all focal elements is carried out. Here, special focal element Φ is treated as a general focal element. The standardized mass function $w - mass_{D1}$ of all focal elements is obtained as follows.

$$w - mass_{D1}(\varphi_i) = \begin{cases} w_{D1} mass_{D1}(\varphi_i), & \varphi_i \neq \Phi \\ 1 - w_{D1} + w_{D1} mass_{D1}(\Phi), & \varphi_i = \Phi \end{cases} \quad (31)$$

where w_{D1} is the importance degree of dimension D1, $w_{D1} = w_1 + w_2 + w_3$.

By the same way, the standardized mass functions of all focal elements on dimension D2 and dimension D3 can also be obtained as $w - mass_{D2}$ and $w - mass_{D3}$.

The standardized mass functions on dimensions D1, D2 and D3 of m alternatives are treated as evidence and combined based on the combination rule shown in Formula (27), thus the mass function of all focal elements under total goal can be obtained as follows.

$$mass(\varphi) = \frac{1}{K} \sum_{\varphi^{(D1)} \cap \varphi^{(D2)} \cap \varphi^{(D3)} = \varphi} w - mass_{D1}(\varphi^{(D1)}) \cdot w - mass_{D2}(\varphi^{(D2)}) \cdot w - mass_{D3}(\varphi^{(D3)}) \quad (32)$$

On discernment frame $\Phi = \{\varphi_1, \varphi_2, \dots, \varphi_m\}$, mass function $mass(\varphi_i)$ means the supportiveness to focal element φ_i

(i.e. alternative i) of all evidences (i.e. standardized mass functions of all focal elements obtained by Formula (29)). Therefore, the sustainability of intelligent manufacturing projects is assessed and the ranking result of m alternatives of intelligent manufacturing project can be obtained by sorting mass functions $mass(\varphi_1), mass(\varphi_2), \dots, mass(\varphi_m)$ in descending order.

IV. CASE STUDY

An air conditioning enterprise in China provides cloud intelligent remote operation and maintenance service project, including real-time remote monitoring of unit operation, automatic prompt of unit abnormality, automatic analysis of big data, construction of the best energy-saving operation scheme, etc. What it faces first in the design phase of intelligent manufacturing implementation is how to select the optimal intelligent manufacturing project in multiple alternatives. The enterprise will carry out SAoIM and select the project with the highest sustainability. It has built a digital twin control structure in its business activities. Therefore, experts can master the digital twin information comprehensively and make a judgment accordingly.

There are eight alternatives (alt. 1: quiet series, alt. 2: sterilization series, alt. 3: energy saving series, alt. 4: intelligent series, alt. 5: humidification series, alt. 6: portable series, alt. 7: large area series and alt. 8: artistic series) of intelligent manufacturing project and four experts to evaluate the sustainability of them on each indicator shown in Fig. 3. All experts are equal.

On indicator I_1 , four experts separately carry out the pairwise comparison of the performance of eight alternatives based on the modified nine-level comparison scale method (Table 2). The TFN-RJMs $E^{(1,1)}, E^{(1,2)}, E^{(1,3)}$ and $E^{(1,4)}$ are given respectively as shown by Tables 3, 4, 5 and 6.

TABLE 3. TFN-RJM $E^{(1,1)}$ (pairwise comparison on indicator I_1 given by expert 1).

Alt.	1	2	3	4	5	6	7	8
1	5/5	2/8	3/7	4/6	5/5	5/5	6/4	7/3
2	-	5/5	6/4	6/4	7/3	7/3	7/3	8/2
3	-	-	5/5	6/4	6/4	6/4	7/3	7/3
4	-	-	-	5/5	5/5	6/4	7/3	6/4
5	-	-	-	-	5/5	5/5	6/4	6/4
6	-	-	-	-	-	5/5	6/4	6/4
7	-	-	-	-	-	-	5/5	6/4
8	-	-	-	-	-	-	-	5/5

TABLE 4. TFN-RJM $E^{(1,2)}$ (pairwise comparison on indicator I_1 given by expert 2).

Alt.	1	2	3	4	5	6	7	8
1	5/5	5/5	5/5	6/4	6/4	7/3	8/2	9/1
2	-	5/5	5/5	5/5	6/4	6/4	6/4	6/4
3	-	-	5/5	6/4	5/5	5/5	8/2	7/3
4	-	-	-	5/5	5/5	6/4	9/1	8/2
5	-	-	-	-	5/5	7/3	5/5	6/4
6	-	-	-	-	-	5/5	6/4	7/3
7	-	-	-	-	-	-	5/5	6/4
8	-	-	-	-	-	-	-	5/5

TABLE 5. TFN-RJM $E^{(1,3)}$ (pairwise comparison on indicator I_1 given by expert 3).

Alt.	1	2	3	4	5	6	7	8
1	5/5	7/3	7/3	6/4	5/5	4/6	3/7	1/9
2	-	5/5	5/5	4/6	4/6	4/6	4/6	3/7
3	-	-	5/5	5/5	4/6	4/6	4/6	3/7
4	-	-	-	5/5	5/5	5/5	4/6	4/6
5	-	-	-	-	5/5	4/6	5/5	3/7
6	-	-	-	-	-	5/5	4/6	3/7
7	-	-	-	-	-	-	5/5	3/7
8	-	-	-	-	-	-	-	5/5

For example, expert 1 gave his judgment opinion of the performance of alt. 2 relative to alt. 1 on indicator I_1 as “strong inferior”, which is expressed as “2/8” as shown in the second column of the first row of $E^{(1,1)}$ (Table 3).

Then consistency test is carried out. $E^{(1,1)}$, $E^{(1,2)}$, $E^{(1,3)}$ and $E^{(1,4)}$ are mapped into real number matrices $DV^{(1,1)}$, $DV^{(1,2)}$, $DV^{(1,3)}$ and $DV^{(1,4)}$. Their consistency ratios are obtained as: $CR(DV^{(1,1)}) = 0.06$, $CR(DV^{(1,2)}) = 0.09$, $CR(DV^{(1,3)}) = 0.08$ and $CR(DV^{(1,4)}) = 0.07$, while all of them pass the consistency test since their consistency ratios are less than 0.1.

TABLE 6. TFN-RJM $E^{(1,4)}$ (pairwise comparison on indicator I_1 given by expert 4).

Alt.	1	2	3	4	5	6	7	8
1	5/5	6/4	6/4	5/5	5/5	4/6	2/8	3/7
2	-	5/5	5/5	4/6	5/5	3/7	2/8	3/7
3	-	-	5/5	5/5	4/6	3/7	2/8	2/8
4	-	-	-	5/5	5/5	4/6	3/7	4/6
5	-	-	-	-	5/5	4/6	3/7	3/7
6	-	-	-	-	-	5/5	2/8	3/7
7	-	-	-	-	-	-	5/5	6/4
8	-	-	-	-	-	-	-	5/5

The preference information of each expert is integrated into a preference information integration matrix as shown in Tables 7 and 8.

By the conversion based on gravity-center formula of TFN, $E^{(1)}$ is converted into gravity-center matrix $\hat{E}^{(1)}$ as shown in Table 9.

The eigenvector of $\hat{E}^{(1)}$ corresponding to its largest eigenvalue is obtained as $\delta(\hat{E}^{(1)}) = [0.3847, 0.3528, 0.3285, 0.3630, 0.2659, 0.3022, 0.4069, 0.4003]^T$. Therefore, the indicator value of the eight alternatives on indicator I_1 is obtained as $[0.1372, 0.1258, 0.1171, 0.1294, 0.0948, 0.1078, 0.1451, 0.1428]^T$. By same way the indicator values of eight alternatives on other indicators is obtained and the indicator value matrix is shown in Table 10.

After determining the indicator value by TFN-AHP, the indicator importance degree will be determined by complex networks and PROMETHEE II as follows.

Multiple experts evaluate whether the relationship between two indicators exists or not. If more than half of the experts think that there is a relationship between two indicators, the two indicators are related and a connection between two corresponding nodes in IndN is added. Finally IndN is obtained and its adjacency matrix is shown by Table 11 in which “1” stands for there is a connection between two nodes while “0” stands for there is no connection between two nodes.

According to the definitions and explanations of ‘degree’, ‘closeness’, ‘betweenness’, ‘pagerank’ and ‘eigenvector’, the five types of centrality property of the nodes in IndN is shown in Table 12.

For the ‘degree’ centrality type (cen^1), the GPF of one node relative to another node is obtained according to Formula (20) and is shown in Table 13. Similarly, for the ‘closeness’ centrality type (cen^2), ‘betweenness’ centrality type (cen^3), ‘pagerank’ centrality type (cen^4) and ‘eigenvector’ centrality type (cen^5), the GPF of one node relative to another node is shown in Tables 14, 15, 16 and 17 respectively.

The PRI of one node relative to another node is obtained according to Formula (21) and is shown in Table 18. Here, $\rho_q = 1/5$ (i.e. the five types of centrality property are treated equally).

TABLE 7. Preference information integration matrix $E^{(1)}$ (columns 1-4).

Alt.	1	2	3	4
1	(1,1,1,1)	(0.9028,1.0640,1.5476,1.9405)	(0.9375,1.1032,1.5989,2.0000)	(0.8571,0.9957,1.3831,1.6667)
2	(1.0030,1.2179,2.0058,2.9167)	(1,1,1,1)	(1.0000,1.0556,1.2143,1.3333)	(0.7143,0.8248,1.1234,1.3333)
3	(0.7946,0.9322,1.3392,1.6667)	(0.8571,0.8846,0.9545,1.0000)	(1,1,1,1)	(1.0000,1.1111,1.4286,1.6667)
4	(0.7143,0.8248,1.1234,1.3333)	(0.8571,0.9957,1.3831,1.6667)	(0.7143,0.7692,0.9091,1.0000)	(1,1,1,1)
5	(0.8571,0.8846,0.9545,1.0000)	(0.6696,0.7735,1.0534,1.2500)	(0.8571,0.9957,1.3831,1.6667)	(1.0000,1.0000,1.0000,1.0000)
6	(0.8125,0.9444,1.3132,1.5833)	(0.7946,0.9878,1.5534,2.0000)	(0.9821,1.1545,1.6688,2.0833)	(0.7143,0.8248,1.1234,1.3333)
7	(1.0933,1.3930,2.4545,3.6071)	(1.0030,1.2735,2.2201,3.2500)	(0.9236,1.1830,2.0989,3.1071)	(0.7153,0.8810,1.3930,1.8125)
8	(1.4653,1.9921,3.1787,3.4792)	(0.8849,1.1073,1.7879,2.3571)	(1.0833,1.3810,2.4359,3.5833)	(0.6349,0.7898,1.2165,1.5238)

TABLE 8. Preference information integration matrix $E^{(1)}$ (columns 5-8).

Alt.	5	6	7	8
1	(1.0000,1.0556,1.2143,1.3333)	(0.8393,0.9835,1.4091,1.7500)	(0.9236,1.1830,2.0989,3.1071)	(1.4653,1.9921,3.1787,3.4792)
2	(0.9821,1.1545,1.6688,2.0833)	(0.7946,0.9878,1.5534,2.0000)	(0.7599,0.9486,1.5022,1.9405)	(0.9583,1.2222,2.1502,3.1667)
3	(0.7143,0.8248,1.1234,1.3333)	(0.6696,0.7735,1.0534,1.2500)	(1.0933,1.3930,2.4545,3.6071)	(0.8403,1.0560,1.7179,2.2738)
4	(1.00,1.00,1.00,1.00)	(0.8571,0.9957,1.3831,1.6667)	(1.5446,2.0989,3.3392,3.6667)	(1.0476,1.3248,2.2900,3.3333)
5	(1,1,1,1)	(0.8393,0.9835,1.4091,1.7500)	(0.8125,0.8889,1.0989,1.2500)	(0.6250,0.7778,1.1978,1.5000)
6	(0.8125,0.9444,1.3132,1.5833)	(1,1,1,1)	(0.6349,0.7898,1.2165,1.5238)	(0.7500,0.9365,1.4835,1.9167)
7	(0.9821,1.0989,1.4545,1.7500)	(1.0476,1.3248,2.2900,3.3333)	(1,1,1,1)	(0.8125,1.0000,1.5275,1.9167)
8	(0.9643,1.1978,1.9091,2.5000)	(0.9196,1.1465,1.8392,2.4167)	(0.6964,0.8681,1.3636,1.7500)	(1,1,1,1)

TABLE 9. Gravity-center matrix $\hat{E}^{(1)}$.

Alt.	1	2	3	4	5	6	7	8
1	1	1.3707	1.4170	1.2299	1.1527	1.2514	1.8537	2.5239
2	1.8100	1	1.1527	1.0018	1.4795	1.3416	1.2953	1.9000
3	1.1889	0.9246	1	1.3053	1.0018	0.9393	2.1659	1.4825
4	1.0018	1.2299	0.8492	1	1.0000	1.2299	2.6574	2.0249
5	0.9246	0.9393	1.2299	1.0000	1	1.2514	1.0148	1.0295
6	1.1674	1.3416	1.4795	1.0018	1.1674	1	1.0457	1.2791
7	2.1659	1.9624	1.8537	1.2081	1.3269	2.0249	1	1.3201
8	2.5239	1.5449	2.1497	1.0457	1.6537	1.5912	1.1760	1

TABLE 10. Indicator value matrix $X = [x_{i,j}]_{8 \times 9}$.

Alt.	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
1	0.1372	0.1550	0.1788	0.0358	0.1586	0.1219	0.0484	0.0598	0.1548
2	0.1258	0.2083	0.2223	0.0456	0.1940	0.2046	0.2470	0.1804	0.0452
3	0.1171	0.1096	0.2546	0.2371	0.2270	0.1670	0.0207	0.2225	0.3068
4	0.1294	0.1919	0.2581	0.2668	0.1123	0.1907	0.1000	0.2214	0.0132
5	0.0948	0.0908	0.0189	0.0421	0.2562	0.2338	0.1933	0.3513	0.0144
6	0.1078	0.1532	0.1584	0.3396	0.3004	0.0744	0.3229	0.2116	0.2718
7	0.1451	0.2752	0.3452	0.1510	0.3158	0.2731	0.1205	0.0636	0.2487
8	0.1428	0.4477	0.1916	0.3436	0.1252	0.3725	0.1951	0.2785	0.3986

As shown in Table 19, the outflow, inflow, net flow of a node in IndN are obtained according to Formulas (22)-(24), then the net flow of all nodes are normalized and lastly the importance degree of the indicator corresponding to each node is obtained according to Formula (25).

Based on the indicator value shown in Table 10 and indicator importance degree shown in Table 19, the two-stage

evidence combination (Fig. 4) is carried out for the assessment of intelligent manufacturing projects. According to Formula (29), the standardized mass functions of all focal elements on each indicator are obtained as shown in Table 20.

Then evidence combination phase 1 is performed according to Formula (30) and the mass functions of all focal

TABLE 11. The adjacency matrix of IndN.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	-	0	0	0	1	1	0	1	1
I_2	0	-	1	1	1	1	1	1	1
I_3	0	1	-	1	1	1	1	1	1
I_4	0	1	1	-	1	1	0	0	0
I_5	1	1	1	1	-	1	0	0	0
I_6	1	1	1	1	1	-	0	0	0
I_7	0	1	1	0	0	0	-	1	1
I_8	1	1	1	0	0	0	1	-	1
I_9	1	1	1	0	0	0	1	1	-

TABLE 12. The five types of centrality property of the nodes in IndN.

	cen^1	cen^2	cen^3	cen^4	cen^5
I_1	0.5000	0.0833	1.3333	0.0909	0.0820
I_2	0.8750	0.1111	3.8333	0.1467	0.1455
I_3	0.8750	0.1111	3.8333	0.1467	0.1455
I_4	0.5000	0.0833	0	0.0894	0.0958
I_5	0.6250	0.0909	1	0.1092	0.1088
I_6	0.6250	0.0909	1	0.1092	0.1088
I_7	0.5000	0.0833	0	0.0894	0.0958
I_8	0.6250	0.0909	1	0.1092	0.1088
I_9	0.6250	0.0909	1	0.1092	0.1088

TABLE 13. The GPF value for the 'degree' centrality type (cen^1).

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	0	0	0	0	0	0
I_2	0.8276	0	0	0.8276	0.5422	0.5422	0.8276	0.5422	0.5422
I_3	0.8276	0	0	0.8276	0.5422	0.5422	0.8276	0.5422	0.5422
I_4	0	0	0	0	0	0	0	0	0
I_5	0.1774	0	0	0.1774	0	0	0.1774	0	0
I_6	0.1774	0	0	0.1774	0	0	0.1774	0	0
I_7	0	0	0	0	0	0	0	0	0
I_8	0.1774	0	0	0.1774	0	0	0.1774	0	0
I_9	0.1774	0	0	0.1774	0	0	0.1774	0	0

TABLE 14. The GPF value for the 'closeness' centrality type (cen^2).

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	0	0	0	0	0	0
I_2	0.0096	0	0	0.0096	0.0051	0.0051	0.0096	0.0051	0.0051
I_3	0.0096	0	0	0.0096	0.0051	0.0051	0.0096	0.0051	0.0051
I_4	0	0	0	0	0	0	0	0	0
I_5	0.0007	0	0	0.0007	0	0	0.0007	0	0
I_6	0.0007	0	0	0.0007	0	0	0.0007	0	0
I_7	0	0	0	0	0	0	0	0	0
I_8	0.0007	0	0	0.0007	0	0	0.0007	0	0
I_9	0.0007	0	0	0.0007	0	0	0.0007	0	0

elements on dimensions D1, D2 and D3 are obtained as shown in Table 21.

According to Formula (31), the standardizations of mass functions $mass_{D1}$, $mass_{D2}$ and $mass_{D3}$ are carried out respectively and the standardized mass functions are shown in Table 22.

TABLE 15. The GPF value for the 'betweenness' centrality type (cen^3).

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	1	0.7506	0.7506	1	0.7506	0.7506
I_2	1	0	0	1	1	1	1	1	1
I_3	1	0	0	1	1	1	1	1	1
I_4	0	0	0	0	0	0	0	0	0
I_5	0	0	0	1	0	0	1	0	0
I_6	0	0	0	1	0	0	1	0	0
I_7	0	0	0	0	0	0	0	0	0
I_8	0	0	0	1	0	0	1	0	0
I_9	0	0	0	1	0	0	1	0	0

TABLE 16. The GPF value for the 'pagerank' centrality type (cen^4).

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	0	0	0	0	0	0
I_2	0.0382	0	0	0.0402	0.0174	0.0174	0.0402	0.0174	0.0174
I_3	0.0382	0	0	0.0402	0.0174	0.0174	0.0402	0.0174	0.0174
I_4	0	0	0	0	0	0	0	0	0
I_5	0.0042	0	0	0.0049	0	0	0.0049	0	0
I_6	0.0042	0	0	0.0049	0	0	0.0049	0	0
I_7	0	0	0	0	0	0	0	0	0
I_8	0.0042	0	0	0.0049	0	0	0.0049	0	0
I_9	0.0042	0	0	0.0049	0	0	0.0049	0	0

TABLE 17. The GPF value for the 'eigenvector' centrality type (cen^5).

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	0	0	0	0	0	0
I_2	0.0492	0	0	0.0304	0.0167	0.0167	0.0304	0.0167	0.0167
I_3	0.0492	0	0	0.0304	0.0167	0.0167	0.0304	0.0167	0.0167
I_4	0.0024	0	0	0	0	0	0	0	0
I_5	0.0090	0	0	0.0021	0	0	0.0021	0	0
I_6	0.0090	0	0	0.0021	0	0	0.0021	0	0
I_7	0.0024	0	0	0	0	0	0	0	0
I_8	0.0090	0	0	0.0021	0	0	0.0021	0	0
I_9	0.0090	0	0	0.0021	0	0	0.0021	0	0

TABLE 18. The PRI value.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9
I_1	0	0	0	1	0.7506	0.7506	1	0.7506	0.7506
I_2	1.9246	0	0	1.9078	1.5814	1.5814	1.9078	1.5814	1.5814
I_3	1.9246	0	0	1.9078	1.5814	1.5814	1.9078	1.5814	1.5814
I_4	0.0024	0	0	0	0	0	0	0	0
I_5	0.1913	0	0	1.1851	0	0	1.1851	0	0
I_6	0.1913	0	0	1.1851	0	0	1.1851	0	0
I_7	0.0024	0	0	0	0	0	0	0	0
I_8	0.1913	0	0	1.1851	0	0	1.1851	0	0
I_9	0.1913	0	0	1.1851	0	0	1.1851	0	0

At last evidence combination phase 2 is performed according to Formula (32) and the mass function of all focal elements under total goal is obtained as shown in Table 23.

TABLE 19. The outflow, inflow, net flow, normalized net flow and importance degree.

	Out_j	In_j	Net_j	Normalized Net_j	Importance degree w_j
I_1	5.0026	4.6190	0.3837	0.4677	0.1146
I_2	12.0656	0	12.0656	0.9000	0.2205
I_3	12.0656	0	12.0656	0.9000	0.2205
I_4	0.0024	9.5560	-9.5536	0.1000	0.0245
I_5	2.5615	3.9134	-1.3519	0.4035	0.0989
I_6	2.5615	3.9134	-1.3519	0.4035	0.0989
I_7	0.0024	9.5560	-9.5536	0.1000	0.0245
I_8	2.5615	3.9134	-1.3519	0.4035	0.0989
I_9	2.5615	3.9134	-1.3519	0.4035	0.0989

The ranking result of eight alternatives of intelligent manufacturing project can be obtained by sorting mass functions $mass(\varphi_1), mass(\varphi_2), \dots, mass(\varphi_8)$ in descending order. Therefore, the SAoIM result of this case is: alt. 8, alt. 7, alt. 4, alt. 2, alt. 3, alt. 6, alt. 1, and alt. 5 as shown in Table 23. Alt. 8 is the optimal alternative of intelligent manufacturing project. From the SAoIM result, alt. 8 ranks first with alt. 7 ranking second, while alt. 5 ranks first-last with alt. 1 ranking second-last. In terms of the indicator value shown in Table 10, alt. 8 ranks first in four indicators (I_2, I_4, I_6 and I_9) and ranks second in two indicators (I_1 and I_8), while alt. 7 ranks first in three indicators (I_1, I_3 and I_5) and ranks second in two indicators (I_2 and I_6); alt. 5 ranks first-last in three indicators (I_1, I_2 and I_3) and ranks second-last in two indicators (I_4 and I_9), while alt. 1 ranks first-last in two indicators (I_4 and I_8) and ranks second-last in two indicators (I_6 and I_7). This is consistent with the SAoIM result, which can prove its validity.

V. DISCUSSIONS

A. COMPARING THE RANKS OF DIFFERENT MODELS

The reliability of the result obtained by the proposed model should be assessed for a final selection of the optimal alternatives. The most common means of assessing the reliability of the result is to compare it with other similar models.

TABLE 20. The standardized mass functions of all focal elements on each indicator.

	$w\text{-}mass_1$	$w\text{-}mass_2$	$w\text{-}mass_3$	$w\text{-}mass_4$	$w\text{-}mass_5$	$w\text{-}mass_6$	$w\text{-}mass_7$	$w\text{-}mass_8$	$w\text{-}mass_9$
φ_1	0.0677	0.0902	0.1043	0.0026	0.0400	0.0317	0.0041	0.0160	0.0454
φ_2	0.0621	0.1213	0.1297	0.0033	0.0489	0.0532	0.0209	0.0484	0.0133
φ_3	0.0578	0.0638	0.1486	0.0171	0.0573	0.0434	0.0018	0.0597	0.0899
φ_4	0.0639	0.1117	0.1506	0.0193	0.0283	0.0496	0.0085	0.0594	0.0039
φ_5	0.0468	0.0529	0.0110	0.0030	0.0646	0.0608	0.0164	0.0942	0.0042
φ_6	0.0532	0.0892	0.0924	0.0245	0.0758	0.0194	0.0273	0.0567	0.0797
φ_7	0.0716	0.1602	0.2014	0.0109	0.0796	0.0710	0.0102	0.0171	0.0729
φ_8	0.0705	0.2607	0.1118	0.0248	0.0316	0.0969	0.0165	0.0747	0.1169
Φ	0.5063	0.0500	0.0500	0.8944	0.5739	0.5739	0.8944	0.5739	0.5739

The discussion of the results is presented using the comparison of three models (PROMETHEE II [43]–[45], TOPSIS [37] and VIKOR [33]). These methods were chosen because they have so far given stable and reliable results. PROMETHEE II, TOPSIS and VIKOR methods were modified using the indicator value and the indicator importance degree obtained by the proposed methods in this paper, which are called M’PROMETHEE II, M’TOPSIS and M’VIKOR. These three models are compared with the proposed model.

The comparison of the ranks of the eight alternatives of intelligent manufacturing project according to the proposed model, M’PROMETHEE II, M’TOPSIS and M’VIKOR is shown in Table 24.

Ranking of the eight alternatives of intelligent manufacturing project according to the models used in order to assess of the reliability of the results shows that alt. 8 remained in first place for the majority of the model (the proposed model, M’PROMETHEE II and M’TOPSIS), while alt. 8 and alt. 7 are the top two alternatives and alt. 1 and alt. 5 are the last two alternatives.

In order to establish the connection between the results obtained using four different models (Tables 24), Spearman’s correlation coefficient (SCC) [32], [31] was used. SCC of ranks is a useful and important indicator for determining the link between the results obtained by different models. Additionally, the case in this study has ordinal variables or ranked variables, while SCC is suitable for use in this situation. In this paper, SCC was used to define the statistical significance of the difference between the ranks obtained by different models. The results of the comparison of ranks using SCC are shown in Tables 25.

The SCC values from Table 25, which are with the average values of 0.8730, show a high correlation between the ranks among the models examined. When SCC values are greater than 0.8 an extremely high correlation is shown [49]. In our case, most of the SCC values are also significantly greater than 0.8 and only the SCC value between the proposed model and M’PROMETHEE II and the SCC value between M’PROMETHEE II and M’VIKOR are 0.7857 (very close to 0.8). Therefore, we can conclude that there is a very high correlation between the proposed model and the other related models.

TABLE 21. The mass functions of all focal elements on each dimension.

	$mass_{D1}$	$mass_{D2}$	$mass_{D3}$
φ_1	0.0883	0.0491	0.0424
φ_2	0.1284	0.0707	0.0502
φ_3	0.0908	0.0764	0.1038
φ_4	0.1363	0.0611	0.0451
φ_5	0.0175	0.0872	0.0721
φ_6	0.0777	0.0751	0.1075
φ_7	0.2316	0.1097	0.0645
φ_8	0.2193	0.0993	0.1431
Φ	0.0100	0.3714	0.3713

TABLE 22. The standardized mass functions of all focal elements on each dimension.

	$w-mass_{D1}$	$w-mass_{D2}$	$w-mass_{D3}$
φ_1	0.0490	0.0109	0.0094
φ_2	0.0713	0.0157	0.0112
φ_3	0.0505	0.0170	0.0231
φ_4	0.0757	0.0136	0.0100
φ_5	0.0097	0.0194	0.0160
φ_6	0.0432	0.0167	0.0239
φ_7	0.1287	0.0244	0.0143
φ_8	0.1219	0.0221	0.0318
Φ	0.4500	0.9841	0.9840

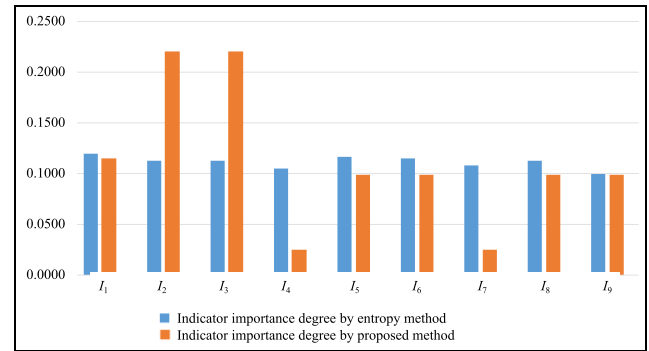
TABLE 23. The mass functions of all focal elements under total goal and the ranking result.

	$mass$	Rank
φ_1 (alt. 1)	0.0517	7
φ_2 (alt. 2)	0.0745	4
φ_3 (alt. 3)	0.0618	5
φ_4 (alt. 4)	0.0769	3
φ_5 (alt. 5)	0.0229	8
φ_6 (alt. 6)	0.0554	6
φ_7 (alt. 7)	0.1319	2
φ_8 (alt. 8)	0.1336	1
Φ	0.3913	/

B. COMPARING THE RANKS USING INDICATOR IMPORTANCE DEGREES DETERMINED BY DIFFERENT METHODS

In order to analyse the effectiveness of the proposed indicator importance degree calculation method, according to the indicator value matrix shown in Table 10, the indicator importance degree determined by entropy method (a typical weighting method [37], [40]) is shown in Table 26.

The indicator importance degree of entropy type is compared with the indicator importance degree determined by the

**FIGURE 6.** The comparison of the indicator importance degree determined by different method.

proposed method (integration of complex networks modeling and PROMETHEE II), and the results are shown in Fig. 6.

According to the indicator importance degree of entropy type, the eight alternatives of intelligent manufacturing project are ranked by the proposed two-stage evidence combination approach, and the result is shown in Table 27.

By comparing the mass function values and the ranking results of alternatives obtained in Tables 23 and 27, it can be seen that when the proposed two-stage evidence combination approach is used, through different importance degree types (the proposed integration of complex networks modeling and PROMETHEE II, entropy method) the two ranking results have slightly difference. Among them, the ranking results of alt. 3 and alt. 6 are different.

It can be seen from Table 26 and Fig. 5 that in the process of calculating the indicator importance degree by entropy method, the importance degrees of all indicators are relatively average. Among them, the importance degrees of I_1 and I_5 are given larger values (0.1192 and 0.1162), while the importance degrees of I_7 and I_9 are relatively small (0.1077 and 0.0998).

However, by the proposed method the importance degrees (Table 19) of I_2 and I_3 are given larger values (both are 0.2205), while the importance degrees of I_4 and I_7 are relatively small (both are 0.0245). As can be intuitively seen from the adjacency matrix of IndN (Table 11), all indicators except I_1 were affected by I_2 and I_3 . Because the indicators I_2 and I_3 are closely related to other indicators, the proposed method gives them a larger importance degree. However, the entropy method does not take into account the interaction between indicators, resulting in unreasonable and inaccurate importance degree value.

From Fig. 5, we can see that the importance degrees of other indicators calculated by the two methods are also different. The indicator importance degree calculated by entropy method is completely based on indicator value information. The larger the dispersion of the indicator value, the smaller the entropy value and the smaller the importance degree given to the indicator. Traditional entropy method is only based on indicator data information, and establishes mathematical deduction to calculate objective importance degree. Although

TABLE 24. The ranks of the eight alternatives of intelligent manufacturing project by different models.

Alt.	Proposed model	M'PROMETHEE II		M'TOPSIS		M'VIKOR	
		Netflow	Rank	Closeness	Rank	Composite value	Rank
1	7	-0.7293	7	0.1780	7	1.0001	7
2	4	-0.2842	5	0.3607	5	0.6576	3
3	5	0.0406	3	0.3753	4	0.8724	5
4	3	-0.3119	6	0.3852	3	0.7037	4
5	8	-1.0187	8	0.0901	8	2.0000	8
6	6	-0.0455	4	0.2570	6	0.9369	6
7	2	0.7311	2	0.7581	2	0.0303	1
8	1	1.6178	1	0.8708	1	0.1637	2

TABLE 25. The results of the comparison of ranks using SCC.

	Proposed model	M'PROMETHEE II	M'TOPSIS	M'VIKOR
Proposed model	1	0.7857	0.9762	0.9524
M'PROMETHEE II	/	1	0.8333	0.7857
M'TOPSIS	/	/	1	0.9048
M'VIKOR	/	/	/	1

TABLE 26. The indicator importance degree determined by entropy method.

	Importance degree w_i
I_1	0.1192
I_2	0.1126
I_3	0.1126
I_4	0.1048
I_5	0.1162
I_6	0.1145
I_7	0.1077
I_8	0.1126
I_9	0.0998

TABLE 27. The SAoIM result using the indicator importance degree by entropy method.

	mass	Rank
φ_1 (alt. 1)	0.0529	7
φ_2 (alt. 2)	0.0750	4
φ_3 (alt. 3)	0.0656	6
φ_4 (alt. 4)	0.0764	3
φ_5 (alt. 5)	0.0376	8
φ_6 (alt. 6)	0.0741	5
φ_7 (alt. 7)	0.1257	2
φ_8 (alt. 8)	0.1456	1
Φ	0.3471	/

this method can effectively transfer the data difference of the indicators, it ignores the interaction between the indicators. In the integration of complex networks modeling and PROMETHEE II, complex networks modeling is used to calculate the centrality of five types, which comprehensively considers the interaction between the indicators. I_2 and I_3 are key factors of normal operation of intelligent manufacturing project considering environmental effects. Therefore, they are given greater importance degree, which is more in line with the actual situation of the design, development and evaluation of intelligent manufacturing project. Considering the relationship between the indicators, the proposed method of determining the indicator importance degree is more reasonable.

C. COMPARING THE RANKS USING INDICATOR VALUES DETERMINED BY DIFFERENT METHODS

To clarify the effectiveness of the proposed TFN-AHP method, the result of the proposed model (using TFN-AHP method) and the result of the compared model (using accurate

scoring) are analyzed. In the compared model the natural numbers shown in Table 1 are adopted to express the judgment of expert and the data in Tables 3, 4, 5 and 6 will be changed accordingly. Based on the changed data, the result using the obtained indicator importance degree (Table 19) and the two-stage evidence combination model (Fig. 4) is shown in Table 28.

As can be seen from Table 23 (ranks using indicator value determined by the proposed TFN-AHP) and Table 28 (ranks using indicator value determined by accurate expert scoring), there is a difference between the two ranks. The compared model is contrary to the proposed model on the ranking of alt. 2 and alt. 4, the ranking of alt. 3 and alt. 6 and the ranking of alt. 1 and alt. 5. The main reason for this difference is the existence of qualitative indicators in the indicator system (Fig. 4). These qualitative indicators are often difficult to be accurate. The error of accurate scoring method is large, which cannot truly reflect the judgment intention of the expert group. In the proposed TFN-AHP method, trapezoidal fuzzy number is used to reflect the fuzzy information of expert

TABLE 28. The mass functions of all focal elements under total goal and the ranking result using indicator value determined by accurate expert scoring.

	<i>mass</i>	Rank
φ_1 (alt. 1)	0.0488	8
φ_2 (alt. 2)	0.0865	3
φ_3 (alt. 3)	0.0603	6
φ_4 (alt. 4)	0.0813	4
φ_5 (alt. 5)	0.0574	7
φ_6 (alt. 6)	0.0711	5
φ_7 (alt. 7)	0.1269	2
φ_8 (alt. 8)	0.1296	1
Φ	0.3381	/

group in the evaluation process, which makes up for the problem of large error in the accurate scoring method, better expresses the judgment intention of the expert group, and is more in line with the actual decision-making environment. Therefore, the proposed TFN-AHP method is more suitable for the actual situation and the evaluation result will be more reasonable.

VI. CONCLUSIONS

Intelligent manufacturing is a major challenge and opportunity for traditional manufacturing enterprise. Taking into account the sustainable development in the future, there is no doubt that SAoIM can play a major role and it is therefore essential to have criteria according to which the optimal intelligent manufacturing project is selected. However, the incompleteness of basic data source, the complexity and ambiguity of real indicators, as well as imprecision in the human cognitive process exist in SAoIM process. Aiming at these problems, this paper presents a SAoIM framework based on the digital twin system of whole life cycle of intelligent manufacturing to solve the incompleteness of basic data source. In the presented SAoIM framework, a novel TFN-AHP approach for treating the ambiguity of expert judgment in indicator value determination by introducing TFN into AHP is proposed, while the complexity of the influence relationship among the indicators is processed by complex networks theory which is integrated into PROMETHEE II for the indicator importance degree determination. Based on the indicator value and the indicator importance degree, evidence theory is used to build a two-stage evidence combination model for intelligent manufacturing project assessing. In case study section, the proposed SAoIM supported by digital twin tested and validated on a study of the intelligent manufacturing project assessment of an air conditioning enterprise in China.

The basic idea of applying algorithms in the decision making process of indicator value determination includes the application of TFN for presenting the judgment of experts. The advantages of applying TFN are numerous. TFN-AHP

facilitates the decision making process exclusively by using TFN for presenting the cognitive ambiguity of experts. In such a way both the complexity and ambiguity that may affect the indicator value and final assessment of alternatives are eliminated. Considering the five types of network properties of each assessment indicator, PROMETHEE II is introduced to determine the importance degree of each indicator. On the one hand, the relationship among multiple indicators is considered synthetically, and the interaction among indicators is analyzed through network properties, which is more objective. On the other hand, PROMETHEE II considers the preference of experts in the evaluation process. This integration can make up for the shortcomings of the previous related research. Additionally, mapping the comprehensive assessment into the two-stage evidence combination model considers the two-tier hierarchy of indicator system and fuses both indicator value and indicator importance degree, which can make full use of the advantages of evidence theory in carrying out reliability reasoning based on uncertain information. The contributions of the study towards advances in manufacturing research are as follows. (1) Identification of potential aspects/criteria of intelligent manufacturing project selection, assessing the relative importance under fuzzy information, and finally, the evaluation followed by the selection of the most favorable intelligent manufacturing project(s) against those criteria under uncertain environment. (2) The proposed framework opens valuable insights and actionable points, helps the management (intelligent manufacturing operator/stakeholders) in paying attention to the key factors, and advance critical issues in order to stay competitive and perform better in the intelligent manufacturing industry.

Since this novel framework and the methodology in it are still underrepresented in the literature related to both digital twin system and MCDM, future research should be based on the following aspects. The future development of intelligent manufacturing will focus more on its impact on human, and the final analysis is to explore whether it can provide a good life for human. Therefore, it is necessary to research the sustainability of intelligent manufacturing oriented for people, such as the chronic and cumulative impact of intelligent manufacturing on human. In addition, the data collection based on digital twin system in the whole life cycle of intelligent manufacturing should be carried out by using the new information computing technology such as internet of things and cloud computing. Because this paper only presents a simple framework for SAoIM, in future the deep research may include: (1) The collection, transmission and analysis of multi-source big data in the whole life cycle of intelligent manufacturing based on digital twin framework will be studied. (2) Based on the decision-making support from the sustainability assessment a sustainability maturity model of intelligent manufacturing in the whole life cycle will be built. (3) The assessment data modeling in the digital twin driven information architecture could be considered to provide a detailed information analyzing methodology. More

data and cases should be used to improve the approach's feasibility and practicality.

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