




Multi-criteria decision-making of manufacturing resources allocation for complex product system based on intuitionistic fuzzy information entropy and TOPSIS

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Received: 19 October 2021 / Accepted: 26 December 2022 / Published online: 25 February 2023
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Abstract

Manufacturing resources allocation (MRA) is important area, and a significant challenge is encountered when considering high value, customized, complex structure and long lifespan of complex product system (CoPS). The relationship between uncertainty factors (i.e., inputs and outputs) of processes in CoPS's manufacturing, operation and maintenance needs comprehensive trade-offs in the preliminary MRA stage. Meanwhile, the CoPS's MRA schemes are contradictory from a customer's perspective with different emphasis on operating cost related to operation and maintenance stage. These problems are unavailable in traditional expressions for model and objective function. In this paper, a new variant of MRA multi-criteria decision-making (MCDM) model of CoPS (MRA&CoPS) is developed to evaluate MRA schemes with considering CoPS's lifecycle. Meanwhile, considering characteristics of CoPS and customer-involved MRA process, the three-layer criteria cumulative model is established. In the proposed method, intuitionistic fuzzy sets (IFSs) based subjective–objective hybrid fuzzy method is presented to deal with uncertainty of evaluation criteria. The weights of criteria are determined by the proposed intuitionistic fuzzy information entropy (IFIE). The hybrid IFIE-TOPSIS method is proposed to obtain the optimum MRA scheme by ranking results. An example of CoPS's MRA in a case enterprise is addressed to verify the rationality and validity of the proposed method. The results show that the proposed method is more preferable and robust in MCDM problem of MRA&CoPS.

Keywords Manufacturing resources allocation · Complex product system · Multi-criteria decision-making · Intuitionistic fuzzy information entropy · TOPSIS

Introduction

Complex product system (CoPS) is a kind of technological system with long processing cycle, high complexity and great value of manufacturing resources, which are produced as customized, one-off or small batched capital goods items, such as aircraft engines, offshore oil equipment and cement equipment, distinct from mass-produced commodity products [1]. The manufacturing resources allocation (MRA) problem occurs in many respects for CoPS project, such as project approval and deliver, project schedule, project profitability and product service life, which relates to various types

of manufacturing resources, such as equipment resources, human resources, design resources, simulation resources and data resources. The single or small batch, complicated structures and long processing cycle are main characteristics of CoPS which leads to a more complex MRA in resource selection, sequencing and evaluation. Further, MRA occupied a core position in the lifecycle of CoPS, so as to guarantee the reliability and service life of CoPS with lower cost.

In traditional MRA activities, most decision-makers usually make their choice from an intuitive point of view or partial information of CoPS lifecycle. However, for a CoPS, the problems are often not so easy and it is necessary to analyze the information in more detail with considering product lifecycle. Moreover, most of the modeling efforts in this area ensured MRA schemes smoothly only in manufacturing resources optimal stage (MROS) and manufacturing resources execution stage (MRES), while without considering the influence of product maintenance stage (PMS) in

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lifecycle [2]. For CoPS in a real life, the complexity of manufacturing resources set drives a higher demand for MRA with less expensive cost and reliability requirements.

MROS-MRES-based strategy may lead to the increasing of operating cost of CoPS which has generated customer's unnecessary expenses and has reduced the reputation of CoPS manufacturing enterprise. Currently, MRA with considering PMS in lifecycle is far more concerned.

- (1) Limited considering phase. Traditional MRA is limited within CoPS manufacturing enterprise and not expanded to permeate in CoPS's lifecycle. In addition, it only focused on procurement cost optimization for manufacturing enterprise but ignored the operating cost optimization for CoPS's lifecycle.
- (2) MROS-MRES-based strategy. MROS-MRES-based strategy evaluates MRA schemes with respect to manufacturing resources execution stage (MRES). It cannot be enhancing CoPS's quality with PMS which usually drives customer's choice of CoPS. Choosing the optimal MRA scheme only with considering MROS and MRES is not benefit for decreasing the lifecycle cost. Therefore, MROS-MRES-based strategy cannot be guaranteed to reduce CoPS's cost in the whole lifecycle.

In terms of the problems mentioned above, motivations of the research can be concluded as follows:

- (1) Propose a multi-criteria MRA evaluation model for CoPS with considering different phases of product lifecycle.
- (2) Develop techniques to solve the proposed MRA model, where the CoPS's multi-criteria are all interrelated in intuitionistic fuzzy environment.

To our best knowledge, there has no research proposed MRA model for CoPS from the view of product lifecycle. This paper contributed a richer MRA&CoPS multi-criteria decision-making (MCDM) model, which considering among MROS, MRES and PMS in product lifecycle. The model mainly focuses on MRA which simultaneously minimum MROS cost, MRES cost and PMS cost when CoPS delivers to customer. An 8-tuple evaluation criteria with respect to MROS, MRES and PMS are proposed to evaluate MRA for CoPS. Meanwhile, a novel fuzzy technique based on intuitionistic fuzzy sets (IFSs) is developed to express the expert preference and the objectivity of criteria in intuitionistic fuzzy environment. What is more, for such multi-criteria decision-making problem, it is desirable to employ information entropy (IE) to obtain criteria weights in intuitionistic fuzzy environment, rather than assign weights by expert experience. Drawing upon this, hybrid intuitionistic fuzzy

information entropy (IFIE) and TOPSIS were often applied to cope with customer-involved MRA process of CoPS.

The remainder of this paper is organized as follows. “[Literature review](#)” presents related works. An overview of the background is summarized in “[Background](#)”. In “[Three-layer criteria cumulative model for MRA&CoPS](#)”, a new variant of MRA multi-criteria decision-making model of CoPS (MRA&CoPS) is proposed to evaluate MRA schemes from CoPS's lifecycle perspective with respect to MROS, MRES and PMS. The model integrated a three-layer criteria cumulative strategy for process layer, component layer and product layer of CoPS. “[The proposed approach](#)” details the proposed approach of IFIE-TOPSIS. An illustrative example is validated in “[Case illustration](#)” and conclusions are given in “[Conclusion](#)”.

Literature review

MRA is one of the most important strategic decisions in manufacturing system that has received the growing attention by researchers [2]. Traditionally, the evaluation criteria of MRA problem focus on MROS and MRES, such as time (makespan, tardiness), stability, cost, and reliability. Thekinen and Panchal [3] proposed a MRA evaluation model for matching service seekers and service providers, such as designers and machine owners, in cloud-based design and manufacturing. Chu [4] introduced a MRA method with knowledge-based fuzzy comprehensive evaluation for aircraft structural parts. The capability of planners, complexity of structural parts, reliability of machine tools and reliability of cutting tools are evaluated in the fuzzy comprehensive evaluation method. Wang [5] considered the credit of resource provider and constructed an resource allocation model to improve the efficiency in the process of trading. Liang [6] considered MRES in remanufacturing systems where the stochastic multi-product disassembly line balancing problem with maximal disassembly profit were studied and a chance-constrained programming model was formulated. Xu [7] proposed a bi-level manufacturing resources allocation model under fuzzy environment to satisfy customers' expectation and to maximize suppliers' profit for short lifecycles product. Fast non-dominated sorting genetic algorithm is employed to solve their model. Considering the ontology-based static manufacturing resource capabilities and the statistical nature of the manufacturing supply chain. Wu [8] proposed a novel Bayesian approach to produce the optimal and robust manufacturing resource allocation plan. Lee [9] presented an intelligent data management-induced resource allocation system with fuzzy logic. Saidi-Mehrabad [10] developed a liner programming for dynamic manufacturing resources allocation; the objective is to minimize

Table 1 Methods and features of studies for MRA problem

References	Methods	Attributes	Stage of lifecycle			Problem environment
			MROS	MRES	PMS	
[8]	Genetic algorithm	1	×	✓	×	Uncertain
[7]	Genetic algorithm	4	✓	✓	×	Uncertain
[11]	Particle swarm optimist	1	×	✓	×	Uncertain
[12]	DEA	3	✓	✓	×	Certain
[4]	Fuzzy comprehensive evaluation method	5	×	×	✓	Uncertain
[10]	Linear programming	7	✓	✓	✓	Certain
[13]	Best worst method AHP	4	✓	×	×	Uncertain
This paper	MCDM	8	✓	✓	✓	Uncertain

machine maintenance and overhead, system reconfiguration, backorder and inventory holding, training and salary of worker costs. Lin and Chiu [11] applied particle swarm optimization algorithm to solve stochastic resource allocation problem for raising productivity. Bi [12] employed DEA method to generate resource allocation and target setting plan for each production unit. Ayyildiz [13] used the hybrid Best Worst Method (BWM) and Pythagorean fuzzy AHP method to determine the weight of metrics, in order to perform evaluation of the supply chain in the globalizing world.

To show the differences of this paper from literatures related to MRA problem, a systematic state-of-the-art reviews the existing works on the MRA problem corresponding to Table 1 in terms of methods, attributes, stage of lifecycle and problem environment.

It can be seen that the current research mainly focuses on manufacturing resources evaluation and optimization for shorter product lifecycle and time-to-market product, which concerns the MRA influence of manufacturing resources optimal stage (MROS) or manufacturing resources execution stage (MRES) without considering the product maintenance stage (PMS). However, CoPS has the characteristic of long lifecycle. The neglect of PMS for CoPS, such as ignoring the operating cost, may increase customer's unnecessary cost and reduce the competitiveness of CoPS manufacturing enterprise. Thus, it is necessary to solve MRA problem from the view of MROS, MRES and PMS for MRA&CoPS. There are little previous studies related to MRA considering MROS, MRES and PMS, for example, saidi-Mehrabad [10] proposed a MRA model that considered the influence of the whole product lifecycle. They only focused on solving MRA problem under certain environment, while information for real-world MRA&CoPS are usually imprecise and vague.

Furthermore, decision of selecting the optimal manufacturing resources options are regarded as a multi-objective optimization problem in most studies. However,

MRA&CoPS relates to long lifecycle with various influence factors which commonly include qualitative criteria in addition to quantitative criteria. Hence, MCDM is preferred for proposed MRA&CoPS. Indeed, MRA decision-making has been extensively studied in the community of expert and intelligent systems. In contrast to optimization model in previous studies with intelligent algorithms, qualitative or quantitative criteria are used to make the most suitable decision among a large number of alternatives for the MRA&CoPS problem. Compared to the linearized model for the assignment of available resources in dynamic manufacturing systems under certain environment [10], the proposed model is integrated with CoPS's complex structure and uncertainty of decision information.

Recently, MCDM has received more attention for evaluation and selection problem. Considering uncertain environment, intuitionistic fuzzy sets and TOPSIS are widely used to solve MCDM problem with uncertain evaluation criteria. Fu [14] proposed a new mechanism to re-construct the published composite indicators, and an interval-valued TOPSIS procedure in conjunction with Shannon entropy objective weights was applied for modifying the value measure of health systems. Dwivedi [15] used a combination of subjective weights and entropy weights for each criterion. Then, added weights of PIS and NIS in the final step of TOPSIS to rank candidates. Garg [16] defined a novel algorithm to solve the MCDM process and illustrated numerical examples related to watershed's hydrological geographical areas, global recruitments problem and so on. Niu [17] introduced two mentality parameters to address the risk attributes and mentality of decision-makers in MCDM process, which was regarded as interval-valued intuitionistic fuzzy numbers. Ulucay [18] considered the occurrences were more than one with the possibility of the same of the different membership and non-membership functions, and defined intuitionistic trapezoidal fuzzy-numbers (ITFM-numbers) in

MCDM problem. Hussain [19] investigated the concept of generalized q -rung orthopair fuzzy sets and group generalized q -rung orthopair fuzzy sets to reduce uncertain errors in the original information to ensure the expert's level of trust and improve the accuracy of final decision in MCDM method technique. Pourmehdi [20] used Analytic Network Process (ANP) and fuzzy TOPSIS to address the performance level of collection centers in reverse logistics, from perspective of sustainability dimensions in supply selection. Roszkowska [21] modified Fuzzy TOPSIS to scoring the negotiation offers in ill-structured negotiation problems. In their research, PIS and NIS are derived from a negotiation theory concept which called BATNA. Joshi [22] defined interval-valued intuitionistic hesitant fuzzy Choquet integral operator to aggregate interval-valued intuitionistic hesitant fuzzy sets (IVIHFS) considering the inter-dependency among the decision criteria, and then used TOPSIS method to rank alternatives in IVIHFS environment. Zhang [23] proposed a rural logistics center location model based on the theory of intuitionistic fuzzy TOPSIS. They calculated weight of decision-makers by rating fuzzy numbers and then determine the weight of the evaluation criteria according to weight of decision-makers. Aikhuele [24] proposed an intuitionistic fuzzy multi-criteria decision-making method to solve failure detection problem. They employed a type of entropy method to calculate weights of criteria, which only consider the membership degree and non-membership degree. Then, they got the relative closeness coefficient based on TOPSIS in intuitionistic fuzzy environment. Awasthi [25] presented a TOPSIS-based MCDM approach for evaluating green supplier under fuzzy environment. The employed linguistic terms to rate criteria and alternatives. Kacprzak [26] used TOPSIS method twice for MCDM problem. The first time it is used to determine the weights of decision-makers and the second time is used to rank alternatives. Chen [27] proposed a MCDM and similarity method between intuitionistic values. They ranked alternatives based on the degree of indeterminacy of each alternative with an extended TOPSIS method. Both the triangular fuzzy number (TFN) and TOPSIS were applied to rank the best alternatives of wind power potential in Weibull distribution model coupled with power law [28].

The research listed above all employed IF-TOPSIS which is mainly for solving selection problems with ranking alternatives by one-layer decision-making. For such problems, the decision-making information can be obtained from the evaluation object comprehensively. However, the structure of CoPS is highly complicated, which is manufactured by many processes with a large number of manufacturing resource alternatives. Assuming that a CoPS is composed of n components $\{C_1, C_2, \dots, C_n\}$, and component C_i ($i \leq n$) is manufactured with m_i process $\{P_i^1, P_i^2, \dots, P_i^{m_i}\}$, process $P_i^{m_j}$ ($m_j \leq m_i$) can be manufactured with $S_i^{m_j}$ kinds of

manufacturing resources $\{R_{i1}^{m_j}, R_{i2}^{m_j}, \dots, R_{iS_i^{m_j}}^{m_j}\}$ and each manufacturing resource has $A_i^{m_j}$ alternatives ($A_i^{m_j} \geq S_i^{m_j}$). The number of MRA schemes alternatives for a CoPS can be calculated as $N = C_{A_i^{m_j}}^{S_i^{m_j}} \times P_i^{m_j} \times n$, which is a large quantity of alternative manufacturing resources combination schemes for a CoPS manufacturing task. Thus, it is difficult for experts to obtain comprehensive evaluation information of CoPS directly, and leads to more complex and time-consuming calculation and evaluation process of MRA&CoPS when employing one-layer method. To make the evaluation process more suitable for MRA&CoPS problem, this paper proposed a three-layer decision-making model, in which MRA schemes are determined through process dimension, component dimension and product dimension.

Background

Intuitionistic fuzzy sets

The theory of intuitionistic fuzzy sets (IFS) is always used in decision-making problem [29]. In IFS theory, positive membership degree, negative membership degree and hesitancy degree are used to describe the membership relationship between individuals and sets [30, 31]. Let X be the universe of discourses. Considering IFSs A in X , the aspects of IFSs discussed by A can be described as follows:

An IFSs A in X is defined as $A = \{(x, u_A(x), v_A(x)) | x \in X, X = \{x_1, x_2, \dots, x_n\}\}$, where $u_A(x) \in [0, 1]$ and $v_A(x) \in [0, 1]$ with the condition $0 \leq u_A(x) + v_A(x) \leq 1, \forall x \in X$. The numbers $u_A(x)$ represent the membership degree of x to A , while the numbers $v_A(x)$ represent the non-membership degree of x to A . For each x to A , subject to $\pi_A(x) = 1 - u_A(x) - v_A(x)$, represents a hesitancy degree of x to A . Obviously, $0 \leq \pi_A(x) \leq 1$.

A small value of $\pi_A(x)$ implies that information about x is more certain. On the other hand, a higher value of the hesitancy degree $\pi_A(x)$ means the information that x holds is more uncertain [32].

Information entropy

Information entropy (IE) is proposed by Shannon to solve effective measurement of information problem and evaluate relative weights between information. In addition, the definition of IE is as follows [33–35].

Let $X = \{(x_k | k = 1, 2, \dots, K)\}$, and the probability of X occurrence is P_k . It is obvious that $0 \leq P_k \leq 1$.

The uncertainty degree of probability can be defined as

$$I(x_k) = \ln \frac{1}{p_k} = -\ln p_k \quad (1)$$

In addition, the information entropy of discrete random variables can be calculated as

$$H(x) = H(p_1 p_2 \dots p_k) = \sum_{k=1}^K p_k I(x_k) = - \sum_{k=1}^K p_k \ln p_k \tag{2}$$

To calculate the weight of each probability event, each information entropy should be transformed to weight value as

$$w_k = \frac{1 - H(x_k)}{K - H(X)} \tag{3}$$

where subject to $0 \leq w_k \leq 1$ and $\sum_{k=1}^K w_k = 1$.

Classical TOPSIS method

The classical TOPSIS method is based on the idea that the best alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution [36, 37]. This method works in the background that each attribute is monotonically increasing or decreasing [38]. Normalization is usually required for using TOPSIS to solve MCDM problem [39, 40]. Assuming that there are n criteria (C_1, C_2, \dots, C_n) and m alternatives (A_1, A_2, \dots, A_m), $X = [x_{ij}]_{m \times n}$ represents the decision matrix. In addition, x_{ij} ($i = 1, 2, \dots, n; j = 1, 2, \dots, m$) denotes the value assigned to the i -th criterion of the j -th alternative. $W = [w_1, w_2, \dots, w_n]$ is the weight of each criterion with the condition $\sum_{i=1}^n w_i = 1$. The detailed steps of TOPSIS are carried out as follows.

Step 1: Normalize the decision matrix to obtain normal matrix $B = [b_{ij}]$.

Step2: Calculate the weighted normalized decision matrix:

$$f_{ij} = w_i b_{ij} \tag{4}$$

where w_i is the weight of the i -th criterion.

Step 3: Determine the positive ideal solution (PIS) and negative ideal solution (NIS):

$$F^+ = \{f_1^+, f_2^+, \dots, f_n^+\} \tag{5}$$

$$F^- = \{f_1^-, f_2^-, \dots, f_n^-\} \tag{6}$$

where F^+ denotes the positive ideal solution and F^- denotes the negative ideal solution. If the i -th criterion is beneficial criterion,

$$f_i^+ = \max\{f_{ij}, j = 1, 2, \dots, m\} \tag{7}$$

$$f_i^- = \min\{f_{ij}, j = 1, 2, \dots, m\} \tag{8}$$

On the contrary, if the i -th criterion is cost criterion,

$$f_i^+ = \min\{f_{ij}, j = 1, 2, \dots, m\} \tag{9}$$

$$f_i^- = \max\{f_{ij}, j = 1, 2, \dots, m\} \tag{10}$$

Step 4: Calculate the distances from each alternative to positive ideal solution and negative ideal solution:

$$D_j^+ = \sqrt{\sum_{i=1}^n (f_{ij} - f_i^+)^2}, j = 1, 2, \dots, m \tag{11}$$

$$D_j^- = \sqrt{\sum_{i=1}^n (f_{ij} - f_i^-)^2}, j = 1, 2, \dots, m \tag{12}$$

where D_j^+ denotes the distance between the j -th alternative and the positive ideal solution, and D_j^- denotes the distance between the j -th alternative and the negative ideal solution.

Step 5: Calculate the relative closeness to the ideal solution:

$$D_j^* = \frac{D_j^-}{D_j^+ + D_j^-} \tag{13}$$

Step 6: Rank the alternatives sorting by the value $D_j^* D_j^*$ in decreasing order.

Three-layer criteria cumulative model for MRA&CoPS

CoPS is produced as customized, one-off, or small batched capital goods items with higher complexity and value [41]. CoPS industries is identified as involving technology-intensive capital goods, systems integration, embedded and largely tacit knowledge and skills, project-based manufacturing, low-volume production (batch produced or individually tailored for specific customers), etc. [42]. Based on these studies of CoPS, reference [43] summarized typical manufacturing process of CoPS, i.e., designing activities oriented by customer, technical preparing, procuring raw materials, manufacturing, delivering and maintenance. The multi-level BOM structure is highly complex with many processes, materials and components requirements. In addition, it needs more manufacturing resources to support for the processes, materials and components in demand, while the cost, quality and time, etc. criteria of provided manufacturing resources are various. Moreover, the CoPS's manufacturing task is decomposed into different sub-tasks and manufactured by

Table 2 Stage division of product-lifecycle-oriented MRA&CoPS

Stage	Stage description	Evaluation criteria
I	Manufacturing resources optimal stage (MROS)	Select MRA schemes based on the design activities and technical preparation
II	Manufacturing resources execution stage (MRES)	Manufacture CoPS by selected manufacturing resources according to the customer's needs, design activities and technical preparation
III	Product maintenance stage (PMS)	Maintain the CoPS in case of quality issue

the internal or outsourcing providers. It is difficult to evaluate manufacturing resources allocation schema from the overall perspective of CoPS lifecycle. Considering the multi-level BOM structure of CoPS, the mathematical models have been proposed to process layer, component layer and product layer.

Although a number of research have proposed MRA evaluation criteria, the currently studies mainly considers criteria in MROS and MRES and neglect criteria in PMS, such as operating cost. However, as mentioned in “[Introduction](#)”, PMS is also important for MRA&CoPS problem. Meanwhile, the current research only consider product layer for MRA problem. In real-life MRA&CoPS problem, data related to the problem are usually provided by resource suppliers. However, it is very difficult for resource suppliers providing data related to MRA&CoPS problem in product layer directly after the complex manufacturing of CoPS. Hence, the three-layer criteria cumulative model is proposed from process layer, component layer and product layer to evaluate manufacturing resources allocation of CoPS.

The CoPS's lifecycle involves MROS, MRES and PMS, so the proposed 8-tuple criteria are summarized from three stages in this section. Further, the proposed evaluation criteria are successively accumulated in process layer, component layer and product layer.

Lifecycle-oriented evaluation criteria of MRA&CoPS

CoPS have long economic lives, lasting up to several decades. Thus, product lifecycle should be considered in MRA activities. According to CoPS's characteristics, this paper lists three stages of product-lifecycle-oriented MRA&CoPS process in [Table 2](#).

As shown in [Table 2](#), there are interactions in the effect of three stages for CoPS. The selected MRA schema in Stage I influence CoPS's manufacturing process in Stage II and Stage III. In the three stages, MRA plays an important role

in many respects of CoPS, such as timeliness and reliability. Therefore, the influence of MRA is not isolated but should be researched with the view of product lifecycle. Hence, the interactive evaluation criteria of MRA&CoPS can be summarized from the three stages, as shown in [Fig. 1](#), where T represents time, MC represents manufacturing cost, Q represents quality, R is reliability, SN represents synergy, SF represents safety, OC represents operating cost and ST represents satisfaction.

Three-layer criteria cumulative model

The evaluation information for MRA&CoPS problem usually derives from resource suppliers. For the reason of the high complexity of CoPS, it is difficult for resource suppliers to provide the data related to resources in product layer. Thus, the traditional evaluation method that evaluates resources performance directly in product layer is not suitable for MRA&CoPS problem. CoPS are composed of series component, which can be completed by some key processes. The performance of CoPS can be accumulated from components, whose performance can be accumulated from each process. In addition, it is easier for resource suppliers to provide related information in process layer before the complex CoPS manufacturing process. Thus, this section proposed a three-layer criteria cumulative model based on the proposed 8-tuple criteria, which evaluate the resources performance from process layer, component layer and product layer.

Assuming that a CoPS: P consists m components C_i ($i = 1, 2, \dots, m$), and a component can be produced by n processes PR_j ($j = 1, 2, \dots, m$). The manufacturing data of P of each criterion can be accumulated from the m components. In addition, the manufacturing data of a component C_i of each criterion can be accumulated from the n processes. The details of three-layer criteria cumulative model are introduced as follows.

Stage I: manufacturing data in process layer.

$$T(PTask_{ij}) = T_1(r_{ij}) + T_2(r_{ij}) \quad (14)$$

$$MC(PTask_{ij}) = MC_1(r_{ij}) + MC_2(r_{ij}) \quad (15)$$

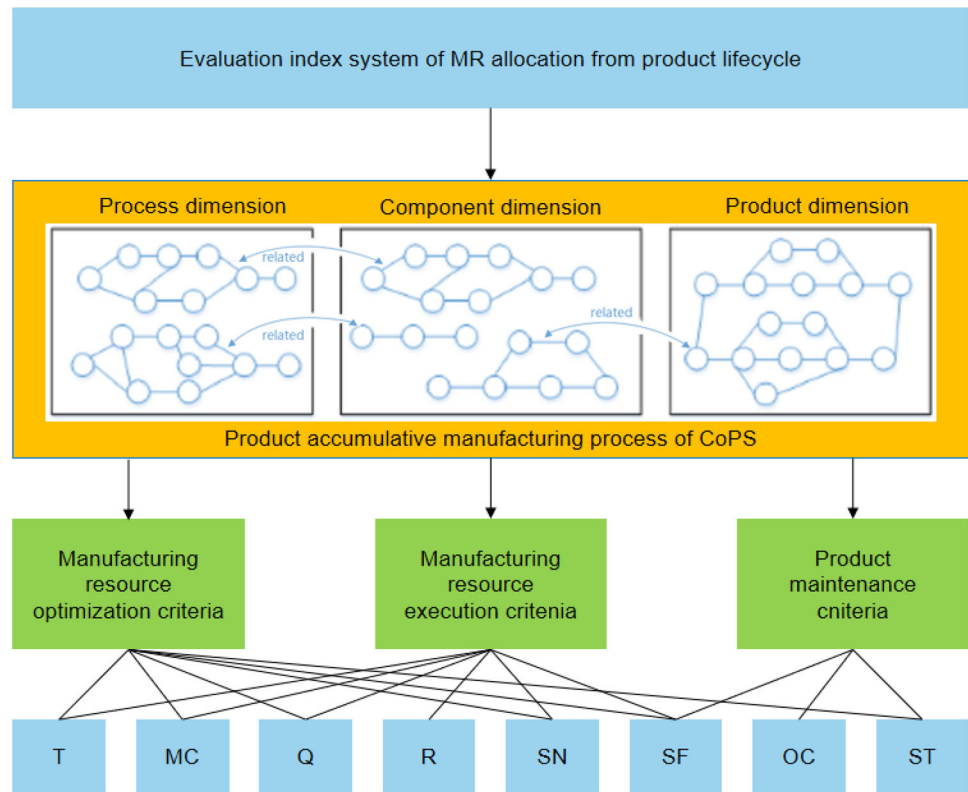
$$Q(PTask_{ij}) = \frac{Q_1(r_{ij}) + Q_2(r_{ij})}{2} \quad (16)$$

$$R(PTask_{ij}) = R_1(r_{ij})R_2(r_{ij}) \quad (17)$$

$$SN(PTask_{ij}) = \frac{SN_1(r_{ij}) + SN_2(r_{ij})}{2} \quad (18)$$

$$SF(PTask_{ij}) = \frac{SF_1(r_{ij}) + SF_2(r_{ij})}{2} \quad (19)$$

Fig. 1 Evaluation criteria of MRA&CoPS



$$ST(PTask_{ij}) = \frac{ST_1(r_{ij}) + ST_2(r_{ij})}{2} \tag{20}$$

In the above equations, $T_1(r_{ij})$ represent the time criterion of manufacturing process, $T_2(r_{ij})$ represents the time criterion of manufacturing resources performance, $MC_1(r_{ij})$ represents the manufacturing costs criterion of manufacturing process, $MC_2(r_{ij})$ represents the manufacturing costs criterion of manufacturing resources performance, $Q_1(r_{ij})$ represents the quality criterion of manufacturing process, $Q_2(r_{ij})$ represents the quality criterion of manufacturing resources performance, $R_1(r_{ij})$ represents the reliability criterion of manufacturing process, $R_2(r_{ij})$ represents the reliability criterion of manufacturing resource performance, $SN_1(r_{ij})$ represents the synergy degree criterion of manufacturing process, $SN_2(r_{ij})$ represents the synergy degree criterion of manufacturing resources performance, $SF_1(r_{ij})$ represents the safety criterion of manufacturing process, $SF_2(r_{ij})$ represents the safety criterion of manufacturing resources performance, $ST_1(r_{ij})$ represents the customer satisfaction criterion of manufacturing process, and $ST_2(r_{ij})$ represents the customer satisfaction criterion of manufacturing resources performance.

Stage II: manufacturing data in component layer.

$$T(MTask_i) = \sum_{j=1}^n T(CTask_{ij}) \tag{21}$$

$$MC(MTask_i) = \sum_{i=1}^m MC(CTask_{ij}) \tag{22}$$

$$Q(CTask_i) = \frac{1}{n} \left[\sum_{k=1}^{n_1} Q(\otimes PTask_{ik}) + \sum_{p=1}^{n_2} \min Q(\oplus PTask_{ip}) \right] \tag{23}$$

$$R(CTask_i) = \prod_{k=1}^{n_1} R(\otimes PTask_{ik}) \prod_{p=1}^{n_2} \min(\oplus PTask_{ip}) \tag{24}$$

$$SN(MTask_i) = \sum_{j=1}^n SN(CTask_{ij})/n \tag{25}$$

$$SF(MTask_i) = \sum_{j=1}^n SF(CTask_{ij})/n \tag{26}$$

$$ST(MTask_i) = \sum_{j=1}^n ST(CTask_{ij})/n \tag{27}$$

In the above equations, \otimes refers to the series branch of a manufacturing task $CTask_i$, n_1 means the total number of process tasks on the series branch, \oplus denotes the parallel branch of a manufacturing task $CTask_i$, n_2 is the total number

of process tasks on the parallel branch, and n_1 plus n_2 is n , whose specific value is related to the structure of $CTask_i$.

Stage III: Criteria value in product layer.

$$T(MTask) = \sum_{i=1}^m T(CTask_i) \quad (28)$$

$$MC(MTask) = \sum_{i=1}^m MC(CTask_i) \quad (29)$$

$$Q(MTask) = \sum_{i=1}^m Q(CTask_i)/m \quad (30)$$

$$R(MTask) = \prod_{i=1}^m R(CTask_i) \quad (31)$$

$$SN(MTask) = \sum_{i=1}^m SN(CTask_i)/m \quad (32)$$

$$SF(MTask) = \sum_{i=1}^m SF(CTask_i)/m \quad (33)$$

$$ST(MTask) = \sum_{i=1}^m ST(CTask_i)/m \quad (34)$$

In the above equations, OC is only calculated in product maintenance stage. It cannot be accumulated as the other seven criteria. In addition, formula (35) is the evaluation methodology of OC [22]:

$$OC(MTask) = c_p L + c_f \sum_{i=1}^L N_i + c_d \left(f_1 \sum_{i=1}^L N_i + f_2 L \right) \quad (35)$$

Formulas (36–38) [25] can be used to describe N_l :

$$N_l = \int_{(1-l)T}^{lT} \lambda^l \quad (36)$$

$$R^l(MTask) = \exp\left(-\int_{(1-l)T}^{lT} \lambda^l dt\right) \quad l = 1, 2, \dots, L \quad (37)$$

$$R^l(MTask) = R(MTask) \quad (38)$$

where $R^l(MTask)$ is the reliability of product in the l -th maintenance stages. λ_l is failure rate of CoPS. Note that formula (36) expresses functional relationship between N_l and λ_l in a preventive maintenance interval. Formula (37) expresses functional relationship between $R^l(MTask)$ and λ_l in the l -th preventive maintenance interval. Formula (38) expresses initial reliability of the CoPS and equals to accumulation reliability criteria of product dimension.

The proposed approach

An improved MCDM approach for MRA&CoPS is proposed, and the approach is mainly divided into the following three stages: (1) preparation stage: DMs determine alternatives (process layer, component layer and product layer), and define evaluation criteria and collect information of criterion for three layers of CoPS. (2) Calculation stage: DMs calculate fuzzy value by fuzzy method proposed in “Fuzzy process” to construct normalized fuzzy decision matrix. Then IE is extended to intuitionistic fuzzy environment as a weighting method to calculate weight of each criterion. Finally, DMs calculate $D_j^* D_j^*$ by TOPSIS in intuitionistic fuzzy environment. (3) Output stage: DMs sort the chosen alternatives by value $D_j^* D_j^*$ in decreasing order and judge the dimension. If the evaluation dimension is product layer, the minimum ranking order is the optimal MRA schema for CoPS. Otherwise, re-evaluate MRA process in next layer. Figure 2 illustrates the conceptual framework of the proposed method.

Fuzzy process

Three-layer criteria proposed in “Three-layer criteria cumulative model for MRA&CoPS” have different types with number and dimension. For example, T is a numerical criterion, while Q is a percentage criterion. Thus, normalization of criteria is necessary for MRA&CoPS. Further, there are various scenario that make the crisp numbers vague and uncertain. For example, the crisp numbers for MRA&CoPS problem is provided by resource suppliers, while the data are usually not constant in actual scenarios. The evaluation data provided by resource suppliers usually represent the average value of the related manufacturing resource historical performance, while the data of certain manufacturing resource for a certain manufacturing process may be variables. Thus, the evaluation criteria data usually have fuzzy phenomenon for MRA&CoPS problem for CoPS enterprises. Meanwhile, in real-life MRA&CoPS process, CoPS enterprises usually have the expectation of each criterion. In this condition, intuitionistic fuzzy sets (IFSs) theory is used in this paper. In addition, how to obtain the membership degree and non-membership degree is the key step of using IFSs. There are several methods to obtain the membership degree and non-membership degree in previous research [44–46]. Moreover, linguistic variable is a widely used method for providing approximate characterization of phenomena that are too complex or ill-defined to be described in conventional quantitative terms [47–49]. In traditional linguistic variable method, only historical data and expert assessment are considered, which leads to inadequate expressions of real-time objectivity data. In this condition, a novel IFS based on subjective–objective hybrid fuzzy method to handle fuzzy phenomenon for MRA&CoPS is proposed in this paper. Table 3 gives the

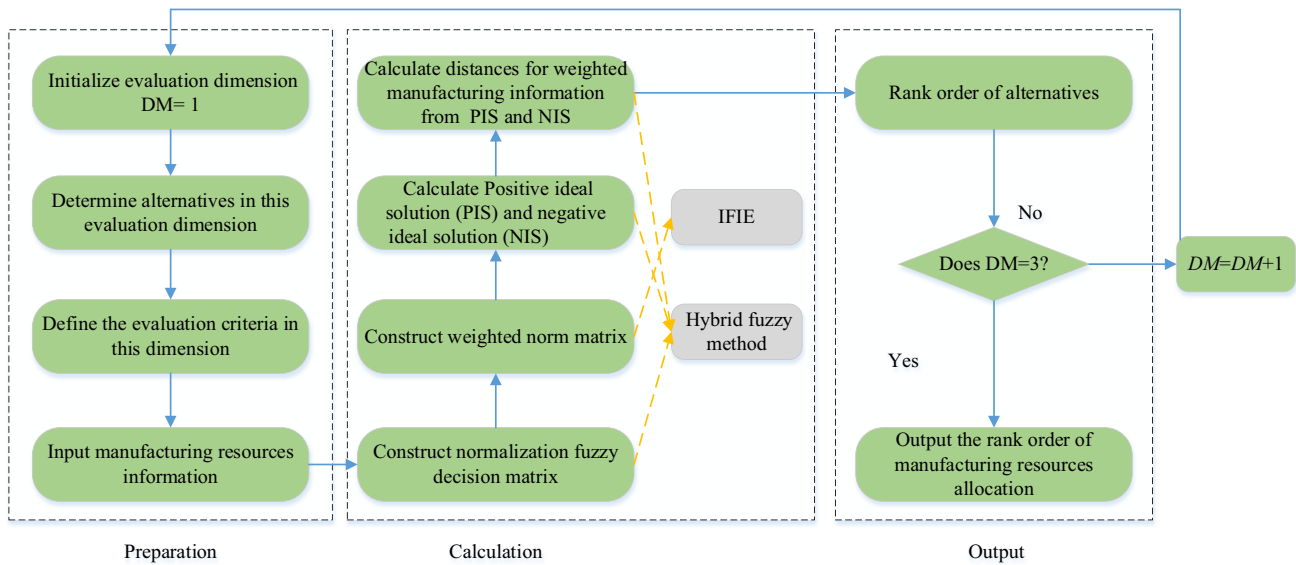


Fig. 2 The conceptual framework of the proposed approach

Table 3 11 levels variable for fuzzy values

Fuzzy scale	Linguistic values	$[u_A(x), v_A(x)]$	Language interval
1	Extremely bad/extremely high	$A_1 = [0.00, 1.00]$	$[0.00, 0.00]$
2	Very bad/very low	$A_2 = [0.10, 0.80]$	$[0.00, 0.15]$
3	Pretty bad/pretty low	$A_3 = [0.20, 0.70]$	$[0.15, 0.40]$
4	Bad/low	$A_4 = [0.30, 0.60]$	$[0.40, 0.45]$
5	Medium bad/medium low	$A_5 = [0.40, 0.50]$	$[0.45, 0.50]$
6	Fair/medium	$A_6 = [0.50, 0.50]$	$[0.50, 0.55]$
7	Medium good/medium high	$A_7 = [0.50, 0.40]$	$[0.55, 0.60]$
8	Good/high	$A_8 = [0.60, 0.30]$	$[0.60, 0.65]$
9	Pretty good/pretty high	$A_9 = [0.70, 0.20]$	$[0.65, 0.90]$
10	Very good/very high	$A_{10} = [0.80, 0.10]$	$[0.90, 1.00]$
11	Extremely good/extremely high	$A_{11} = [1.00, 0.00]$	$[1.00, 1.00]$

11 levels linguistic variable and Eqs. (39–41) are employed to calculate the number of membership degree and non-membership degree:

$$LD_n^m = \frac{D_n^m - E_{min}^m}{E_{max}^m - E_{min}^m} \tag{39}$$

$$E_{min}^m = \frac{E_{min_1}^m + E_{min_2}^m + \dots + E_{min_e}^m}{e} \tag{40}$$

$$E_{max}^m = \frac{E_{max_1}^m + E_{max_2}^m + \dots + E_{max_e}^m}{e} \tag{41}$$

where LD_{mn} is the language value of criteria m for manufacturing resource n , D_{mn} is the evaluation value of criteria m for manufacturing resource n , E_{min}^m is the lower limit of expected interval of criteria m , E_{max}^m is the upper limit of expected interval of criteria m , $E_{min_i}^m$ is the lower limit of

expected interval of criteria m given by the i -th expert ($i = 1, 2, \dots, e$), and $E_{max_i}^m$ is the upper limit of expected interval of criteria m given by the i -th expert. In addition, the process of the hybrid fuzzy method to obtain $[u_a(x), v_a(x)]$ of D_n^m is shown in Fig. 3.

Weight obtaining method

By the fuzzy processing in “Classical TOPSIS method”, standard evaluation criteria are given. In addition, weight of each evaluation criterion is vital for MCDM problem. There are numerous research that have focused on obtaining weights in MCDM problem [39, 46, 50]. Information entropy (IE) theory is a useful tool to obtain weights of each criterion. However, evaluation data of MRA are handled in fuzzy environment. Thus, IE theory should be extended into

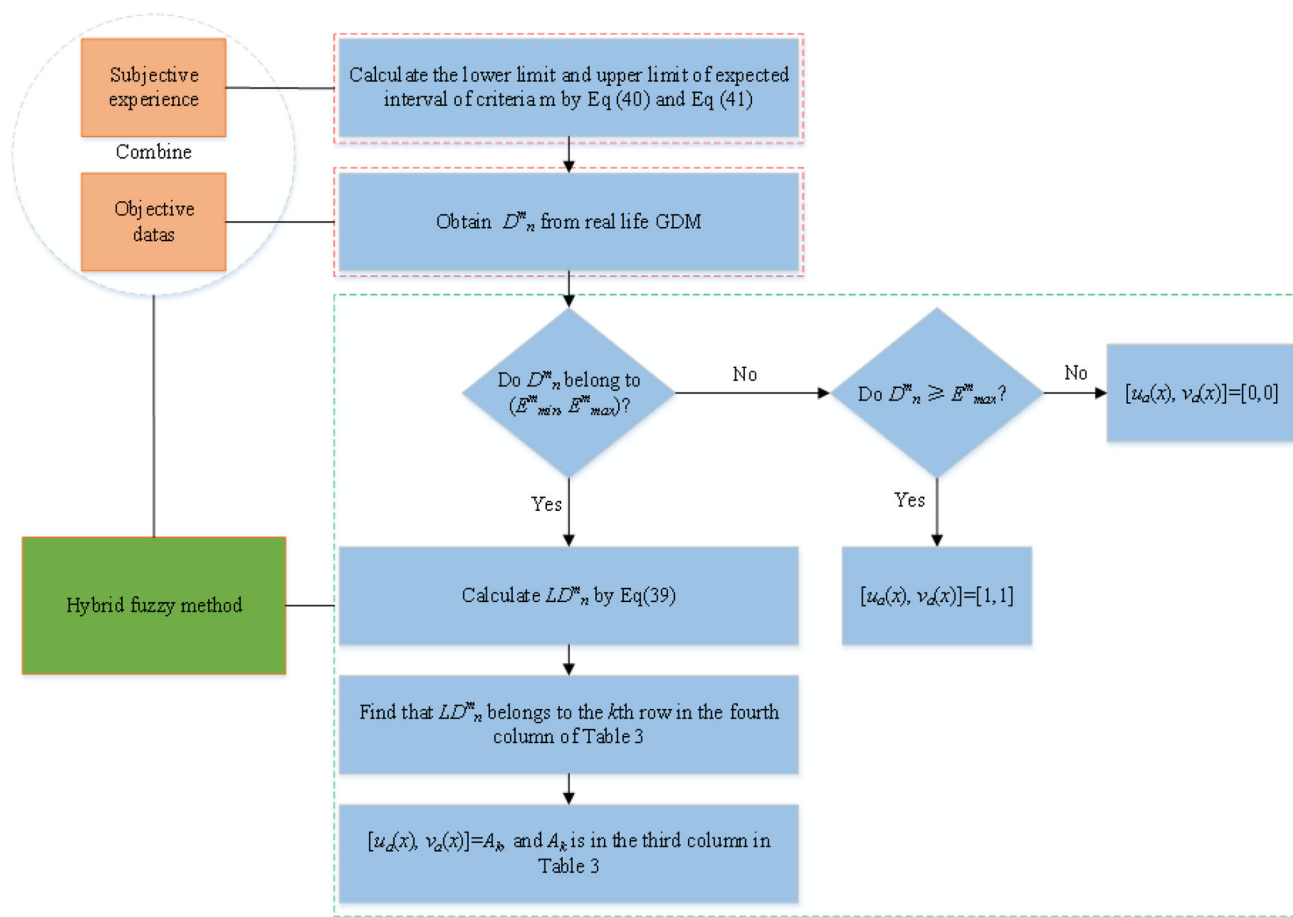


Fig. 3 The process of the subjective–objective hybrid fuzzy method

intuitionistic environment and be used for evaluating fuzzy criteria. The proposed IFIE method is described as follows:

Let intuitionistic fuzzy sets denote $A = \{x, u_A(x), v_A(x) | x \in X\}$. In addition, characteristics of sets A in different situations are shown in Table 4.

Let $X_A = \{x_k | k = 1, 2, \dots, K\}$, and $A_k = \{x_k, u_A(x_k), v_A(x_k) | x_k \in X\}$, where A_k is intuitionistic fuzzy sets of X_A . Therefore, intuitionistic fuzzy information entropy [23] $H(A)$ can be defined as formula (42):

$$H(X_A) = \sum_{k=1}^K H(A_k) \tag{44}$$

The proposed IFIE-TOPSIS method

The novel IFIE-TOPSIS method for MRA&CoPS is proposed in this section. First, an 8-tuple evaluation criteria of

$$H(A_k) \begin{cases} -u_A(x_k) \ln u_A(x_k) - v_A(x_k) \ln v_A(x_k) - \pi_A(x_k) \ln \pi_A(x_k) & u_A(x_k) + v_A(x_k) \in (0, 1) \\ 0 & u_A(x_k) + v_A(x_k) = 1 \\ 0 & u_A(x_k) + v_A(x_k) = 0 \end{cases} \tag{42}$$

In addition, the weight of intuitionistic fuzzy information entropy can be defined as

$$w_k^A = \frac{1 - H(A_k)}{K - H(X_A)} \tag{43}$$

MRA&CoPS is proposed with considering product lifecycle. According to “Lifecycle-oriented evaluation criteria of MRA&CoPS”, the criteria data of CoPS can be accumulated from process layer, component layer and product layer in a production logic sequence. Based on IFSs theory, the subjective–objective hybrid fuzzy method is proposed in “Fuzzy

Table 4 Characteristics of sets A in different situations

Characteristics	$u_A(x) \rightarrow 1, v_A(x) \rightarrow 0$	$u_A(x) \rightarrow 0, v_A(x) \rightarrow 1$	$u_A(x) \rightarrow 0, v_A(x) \rightarrow 0$
Membership degree	high	Low	Low
Non-membership degree	Low	High	Low
Hesitancy degree	Low	Low	High
The probability of the event	High	Low	×

Table 5 Manufacturing resources data matrix

Criteria	r_1	r_2	...	r_q
<i>T</i>	a_{11}	a_{12}	...	a_{1q}
<i>MC</i>	a_{21}	a_{22}	...	a_{2q}
<i>Q</i>	a_{31}	a_{32}	...	a_{3q}
<i>R</i>	a_{41}	a_{42}	...	a_{4q}
<i>SN</i>	a_{51}	a_{52}	...	a_{5q}
<i>SF</i>	a_{61}	a_{62}	...	a_{6q}
<i>OC</i>	a_{71}	a_{72}	...	a_{7q}
<i>ST</i>	a_{81}	a_{82}	...	a_{8q}

Table 6 Normalized fuzzy decision matrix

Criteria	r_1	r_2	...	r_q
<i>T</i>	(u_{11}, v_{11})	(u_{12}, v_{12})	...	(u_{1q}, v_{1q})
<i>MC</i>	(u_{21}, v_{21})	(u_{22}, v_{22})	...	(u_{2q}, v_{2q})
<i>Q</i>	(u_{31}, v_{31})	(u_{32}, v_{32})	...	(u_{3q}, v_{3q})
<i>R</i>	(u_{41}, v_{41})	(u_{42}, v_{42})	...	(u_{4q}, v_{4q})
<i>SN</i>	(u_{51}, v_{51})	(u_{52}, v_{52})	...	(u_{5q}, v_{5q})
<i>SF</i>	(u_{61}, v_{61})	(u_{62}, v_{62})	...	(u_{6q}, v_{6q})
<i>OC</i>	(u_{71}, v_{71})	(u_{72}, v_{72})	...	(u_{7q}, v_{7q})
<i>ST</i>	(u_{81}, v_{81})	(u_{82}, v_{82})	...	(u_{8q}, v_{8q})

process” to deal with the fuzzy problem for three-layer criteria cumulative model of MRA&CoPS. Meanwhile, IE is extended in fuzzy environment in “Weight obtaining method” to obtain weights of evaluation criteria for IFIE-TOPSIS approach. The proposed evaluation method consists of the following steps.

Step 1 Initialize evaluation layer, i.e., $DM =$ process layer.

Step 2 Construct manufacturing resources data matrix. Assuming that there are q manufacturing resources $R = (r_1, r_2, \dots, r_q)$ to be evaluated. In addition, the 8-tuple criteria ($T, MC, Q, R, SN, SF, OC, and ST$) is used for MRA&CoPS. The manufacturing resources data matrix $A = [a_{ij}]_{8 \times q}$ can be constructed in Table 5.

Step 3 Construct normalized fuzzy decision matrix.

Calculate the intuitionistic fuzzy values $[u_A, v_A]$ of each evaluation resources for each criterion according to the process in Fig. 3. In addition, the normalized fuzzy decision matrix $B = (b_{ij})_{8 \times q} = (u_{ij}, v_{ij})_{8 \times q}$ is given in Table 6, where u_{ij} donates the membership degree of the i -th criterion of the j -th manufacturing resources and v_{ij} represents the non-membership degree of the i -th criterion of the j -th manufacturing resources.

Step 4 Construct weighted normalized matrix based on IFIE.

The w_{ij} represents the weight of the i -th criterion of the j -th manufacturing resources can be calculated as

$$w_{ij} = \frac{1 - H(A_i)}{8 - \sum_{i=1}^8 H(A_i)} \tag{45}$$

where

$$H(A_i) = \sum_{j=1}^q H(A_{ij}) \tag{46}$$

In addition, $H(A_{ij})$ is the intuitionistic fuzzy information entropy of manufacturing resources data of manufacturing resources data mr_{ij} ($i = 1, 2, \dots, 8; j = 1, 2, \dots, q$). w_{ij} are subject to Eqs. (47) and (48):

$$\sum_{i=1}^8 w_{ij} = 1 \tag{47}$$

$$w_{ix} = w_{iy} \quad x, y = (1, 2, \dots, q) \tag{48}$$

Then, weighted matrix [5] can be given by

$$f_{ij} = (u_{f_{ij}}, v_{f_{ij}}) = w_{ij}b_{ij} = w_{ij}(u_{ij}, v_{ij}) = (1 - (1 - u_{ij})^{w_{ij}}, (v_{ij})^{w_{ij}}), \quad (i = 1, 2, \dots, 8; j = 1, 2, \dots, q) \tag{49}$$

Step 5 Calculate positive ideal solution F^+ and negative ideal solution F^- :

$$F^+ = \{f_1^+, f_2^+, \dots, f_8^+\} \tag{50}$$

$$F^- = \{f_1^-, f_2^-, \dots, f_8^-\} \tag{51}$$

In the 8-tuple criteria, Q, R, SN, SF and ST are beneficial criteria, of whose f_i^+ and f_i^- can be calculated as

$$f_i^+ = (u_{f_i}^+, v_{f_i}^+) = \max\{u_{ij}, v_{ij}\}, j = 1, 2, \dots, q \quad (52)$$

$$f_i^- = (u_{f_i}^-, v_{f_i}^-) = \min\{u_{ij}, v_{ij}\}, j = 1, 2, \dots, q \quad (53)$$

On the contrary, T, MC, OC are cost criteria, and the f_i^+ and f_i^- can be calculated as

$$f_i^+ = (u_{f_i}^+, v_{f_i}^+) = \min\{u_{ij}, v_{ij}\}, j = 1, 2, \dots, q \quad (54)$$

$$f_i^- = (u_{f_i}^-, v_{f_i}^-) = \max\{u_{ij}, v_{ij}\}, j = 1, 2, \dots, q \quad (55)$$

Note that the definition for determining maximum and minimum of $\{u_{ij}, v_{ij}\}$. Assuming that two intuitionistic fuzzy number $a = (u_a, v_a)$ and $b = (u_b, v_b)$, whose intuitionistic fuzzy information entropy are $h(a)$ and $h(b)$, respectively. If $h(a) < h(b)$, then $a > b$. Otherwise, if $h(a) > h(b)$, then $a < b$.

Step 6 Calculate the distance from each alternative to positive ideal solution and negative ideal solution:

$$D_j^+ = \sqrt{\frac{1}{8} \sum_{i=1}^8 \{(u_{f_{ij}} - u_{f_i}^+)^2 + (v_{f_{ij}} - v_{f_i}^+)^2 + (\pi_{f_{ij}} - \pi_{f_i}^+)^2\}} \quad (56)$$

$$D_j^- = \sqrt{\frac{1}{8} \sum_{i=1}^8 \{(u_{f_{ij}} - u_{f_i}^-)^2 + (v_{f_{ij}} - v_{f_i}^-)^2 + (\pi_{f_{ij}} - \pi_{f_i}^-)^2\}} \quad (57)$$

$$\pi_{f_{ij}} = 1 - u_{f_{ij}} - v_{f_{ij}} \quad (58)$$

$$\pi_{f_i}^+ = 1 - u_{f_i}^+ - v_{f_i}^+ \quad (59)$$

$$\pi_{f_i}^- = 1 - u_{f_i}^- - v_{f_i}^- \quad (60)$$

Step 7 Rank the alternatives by D_j^* .

$$D_j^* = \frac{D_j^-}{D_j^+ + D_j^-}, j = 1, 2, \dots, n \quad (61)$$

Step 8 Select optimum manufacturing resources in next layer.

Step 9 Terminate judging. If the evaluation is not over, turn to step 10, otherwise, turn to step 13.

Step 10 Judge the dimension of the upper level. If the dimension of the upper level is the process dimension, let $DM =$ component layer and turn to step 11, and if the dimension of the upper level is the component dimension, let $DM =$ product and turn to step 12.

Step 11 Combine component from the process layer, and turn to step 2.

Step 12 Combine product from the component layer, and turn to step 2.

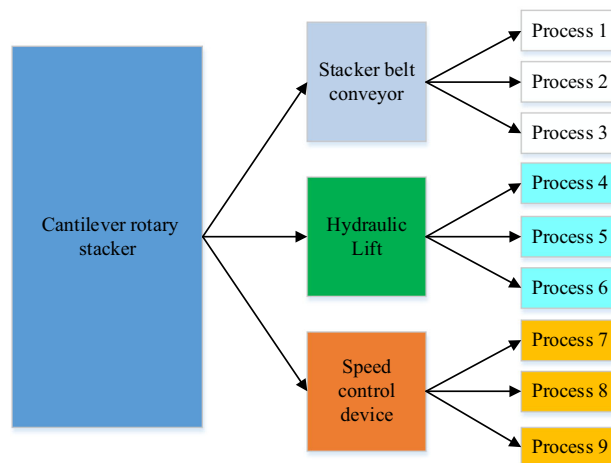


Fig. 4 The structure of the case product

Step 13 Output ideal solutions: the ideal solution includes the ideal scheme in the product dimension and corresponding MRA schema in component layer and process layer.

Case illustration

This section illustrates a case example to demonstrate the effectiveness of the proposed method to optimize MRA&CoPS. In this study, the case product cantilever rotary stacker produced by the case manufacturing enterprise in Tianjin of China is presented to test and to show the applicability and effectiveness of proposed model. The main manufacturing product of the case manufacturing enterprise is complicated and costly equipment, such as cement equipment, metallurgy equipment, and coal equipment. In addition, the customer may refuse to pay the warranty if the product broke down during one to two warranty periods. As Fig. 4 shows, the case product is mainly composed of stacker belt conveyor, hydraulic lift and belt speed control device, each of which is mainly composed by three key processes. In addition, each process can be completed by several kinds of different resources. To simplify the explanation and make this section easier to read, “Process layer” and “Component layer” will only illustrate the resource combination optimization process of stacker belt in process layer and component layer. “Product layer” will illustrate the resource allocation process of the case product.

Evaluation process of three-layer criteria cumulative model

Process layer

Step 1 Determine criteria and obtain data in process layer.

Table 7 The manufacturing data of the criteria for stacker belt conveyor

	Process 1				Process 2				Process 3			
	R_{11}	R_{12}	R_{13}	R_{14}	R_{21}	R_{22}	R_{23}	R_{24}	R_{31}	R_{32}	R_{33}	R_{34}
T (h)	6.3	9.1	5.5	9.2	5.6	9.2	9.8	5.6	9.6	6.1	6.2	9.4
MC (¥)	216.5	218	202	204.5	202.5	204.5	216	202	203.5	203	203	205.5
Q	0.96	0.975	0.955	0.97	0.96	0.955	0.995	0.975	0.995	0.99	0.955	0.96
R	0.915	0.94	0.925	0.99	0.94	0.925	0.915	0.96	0.97	0.925	0.94	0.95
SN	0.75	0.94	0.96	0.70	0.65	0.65	0.78	0.67	0.69	0.70	0.66	0.98
SF	0.97	0.955	0.955	0.965	0.995	0.995	0.975	0.955	0.955	0.955	0.96	0.955
ST	0.85	0.81	0.96	0.90	0.90	0.90	0.96	0.85	0.82	0.81	0.95	0.97

Table 8 The expected interval of each criterion

Criteria	T (h)	MC (¥)	Q	R	SN	SF	ST
Expect interval	(0, 10)	(180, 220)	(0.9, 1)	(0.8, 1)	(0.2, 1)	(0.9, 1)	(0.5, 1)

Table 9 Weights of each criterion in process dimension

Criteria	T	MC	Q	R	SN	SF	ST
Weights	0.1308	0.1509	0.1432	0.1462	0.1455	0.1496	0.1337

The evaluation criteria in process layer of the case component are selected from manufacturing resources optimization criteria and manufacturing resources execution criteria, as shown in Fig. 1, i.e., T , MC , Q , R , SN , SF and ST . As Fig. 4 shows, the case component can be completed by three key processes and each process has to be completed by 4 kinds of manufacturing resources. The manufacturing data of these criteria for the case component is shown in Table 7.

Step 2 Fuzzy process.

As mentioned in “Fuzzy process”, the novel IFSs based subjective–objective hybrid fuzzy is applied to handle the fuzzy phenomenon of MRA. The decision-makers implement the process in Fig. 3 to transform the value shown in Table 7 to fuzzy value described in Table 2. The expected interval of each criterion is shown in Table 8 for fuzzy process. In addition, the normalization fuzzy decision matrix which is composed of the fuzzy value in “The proposed IFIE–TOPSIS method” can be found in the Tables 15, 16.

Step 3 Determine criteria weights by IFIE method.

IFIE method is proposed to determine the weights of each criterion in process layer. Criteria weights are obtained according to the details in “Weight obtaining method”. Resulting weights of the process layer are given in Table 9.

Step 4 Evaluation MRA schema by hybrid IFIE–TOPSIS approach.

In this step, the ranking result of MRA is obtained by the proposed IFIE–TOPSIS approach. The weighted norm matrix in process layer is calculated according to formula (49). The ranking result in process layer is computed according to “The proposed IFIE–TOPSIS method” and is shown in Table 10.

Component layer

Based on the evaluation result of process layer and bill of material (BOM) structure of the case component, the top 2 optimal resources in each process, i.e., R_{13} and R_{14} in process 1, R_{21} and R_{24} in process 2, R_{34} and R_{32} in process 3,

Table 10 Ranking result in process dimension

Process 1			Process 2			Process 3		
Resources	D_i^*	Rank	Resources	D_i^*	Rank	Resources	D_i^*	Rank
R_{11}	0.4004	3	R_{21}	0.5965	1	R_{31}	0.4450	4
R_{12}	0.3807	4	R_{22}	0.5131	3	R_{32}	0.5193	2
R_{13}	0.6019	1	R_{23}	0.4989	4	R_{33}	0.4455	3
R_{14}	0.5425	2	R_{24}	0.5221	2	R_{34}	0.5463	1

Table 11 Ranking result in component dimension

Resources combinations	$D^* i$	Rank
(R_{13}, R_{21}, R_{34})	0.4003	6
(R_{13}, R_{21}, R_{32})	0.3791	7
(R_{13}, R_{24}, R_{34})	0.4992	3
(R_{13}, R_{24}, R_{32})	0.4542	5
(R_{14}, R_{21}, R_{34})	0.3041	8
(R_{14}, R_{21}, R_{32})	0.4808	4
(R_{14}, R_{24}, R_{34})	0.5911	1
(R_{14}, R_{24}, R_{32})	0.5264	2

are selected for component layer accumulation. As the case component is completed by the three key processes, then the selected 6 resources can be combined into 8 resources combinations, i.e., (R_{13}, R_{21}, R_{34}) , (R_{13}, R_{21}, R_{32}) , (R_{13}, R_{24}, R_{34}) , (R_{13}, R_{24}, R_{32}) , (R_{14}, R_{21}, R_{34}) , (R_{14}, R_{21}, R_{32}) , (R_{14}, R_{24}, R_{34}) , (R_{14}, R_{24}, R_{32}) . In this paper, for the simplification of evaluating process, the 8 resources combinations are evaluated in component layer. The evaluation step in component layer is the same as the evaluation step in process layer as represented in “Process layer”. The normalization fuzzy decision matrix in component layer is shown in Table 16. The ranking result in component layer is shown in Table 11.

Product layer

In order to simplify the problem, the top 2 optimal resources combination schemes in each component are selected to be evaluated in product layer. Based on the evaluation result of component layer of the case component in Table 11, the two chosen resources combination schemes of stacker belt conveyor are (R_{14}, R_{24}, R_{34}) and (R_{14}, R_{24}, R_{32}) . As shown in Fig. 4, the case product is composed of three key components. Based on the manufacturing data of the other two components (see in Tables 18 and 19) and calculated as the case component shown in “Process layer” and “Component layer”, the two chosen resources combination schemes of hydraulic lift are (R_{42}, R_{51}, R_{61}) and (R_{42}, R_{51}, R_{64}) , as the two chosen resources combination schemes of speed control device are (R_{74}, R_{81}, R_{92}) and (R_{73}, R_{84}, R_{92}) . Thus, there are 8 resources combination schemes, i.e., $RC_1 = \{(R_{14}, R_{24}, R_{34}), (R_{42}, R_{51}, R_{61}), (R_{74}, R_{81}, R_{92})\}$, $RC_2 = \{(R_{14}, R_{24}, R_{34}), (R_{42}, R_{51}, R_{61}), (R_{73}, R_{84}, R_{92})\}$, $RC_3 = \{(R_{14}, R_{24}, R_{34}), (R_{42}, R_{51}, R_{64}), (R_{74}, R_{81}, R_{92})\}$, $RC_4 = \{(R_{14}, R_{24}, R_{34}), (R_{42}, R_{51}, R_{64}), (R_{73}, R_{84}, R_{92})\}$, $RC_5 = \{(R_{14}, R_{24}, R_{32}), (R_{42}, R_{51}, R_{61}), (R_{74}, R_{81}, R_{92})\}$, $RC_6 = \{(R_{14}, R_{24}, R_{32}), (R_{42}, R_{51}, R_{61}), (R_{73}, R_{84}, R_{92})\}$, $RC_7 = \{(R_{14}, R_{24}, R_{32}), (R_{42}, R_{51}, R_{64}), (R_{74}, R_{81}, R_{92})\}$, $RC_8 = \{(R_{14}, R_{24}, R_{32}), (R_{42}, R_{51}, R_{64}), (R_{73}, R_{84}, R_{92})\}$ to be evaluated in product layer. The evaluation step of product layer is the same as

Table 12 Ranking result by IFIE-TOPSIS

Scheme	D_i^*	Rank
RC_1	0.6134	1
RC_2	0.5195	3
RC_3	0.5370	2
RC_4	0.3549	5
RC_5	0.3113	7
RC_6	0.3429	6
RC_7	0.2604	8
RC_8	0.3959	4

the evaluation step of process layer as described in “Process layer”. Note that criterion operating cost (OC) is classified in operating cost criteria and it is only evaluated in product layer. The normalization fuzzy decision matrix in product layer is shown in Table 17. In addition, the ranking result in product layer is shown in Table 12.

The final results of the proposed method are summarized in Tables 12. The ranking order of resources combination schemes to manufacture the case product is as follows:

$$RC_1 > RC_3 > RC_2 > RC_8 > RC_4 > RC_6 > RC_5 > RC_7.$$

Hence, it can conclude that the optimal resources combination scheme for the case product is RC_1 , i.e., $\{(R_{14}, R_{24}, R_{34}), (R_{42}, R_{51}, R_{64}), (R_{74}, R_{81}, R_{92})\}$.

IFIE-TOPSIS compared with the traditional TOPSIS

The traditional TOPSIS approach, for which language values are calculated by formula (39) as the elements of the normalization decision matrix and weights of criteria are determined by information entropy, are compared with the proposed IFIE-TOPSIS approach in this section. In the comparing test, the traditional TOPSIS approach is employed in process layer, component layer and product layer to rank the MRA schema for the same product evaluated in “Evaluation process of three-layer criteria cumulative model”. The details of traditional TOPSIS approach in each dimension are introduced in “Classical TOPSIS method” and the steps of weights determination by information entropy are detailed in “Information entropy”. The manufacturing resources data to be evaluated by the traditional TOPSIS approach is same as the data calculated in “Evaluation process of three-layer criteria cumulative model” and shown in Table 7. The selected resources combination schemes to be evaluated in product layer after evaluation in process layer and component layer are shown in Table 13. The normalization real decision matrix expressed by language value of these resources’ combination schemes of each criterion in product layer are shown in Table 20. The optimal resources combination scheme evaluation by the traditional TOPSIS is RC_7 .

Table 13 The selected resources combination schemes

Schemes	Resources combinations		
RC'_1	(R_{14}, R_{21}, R_{31})	(R_{42}, R_{51}, R_{63})	(R_{74}, R_{83}, R_{91})
RC'_2	(R_{14}, R_{21}, R_{31})	(R_{42}, R_{51}, R_{63})	(R_{72}, R_{83}, R_{91})
RC'_3	(R_{14}, R_{21}, R_{31})	(R_{42}, R_{53}, R_{63})	(R_{74}, R_{83}, R_{91})
RC'_4	(R_{14}, R_{21}, R_{31})	(R_{42}, R_{53}, R_{63})	(R_{72}, R_{83}, R_{91})
RC'_5	(R_{13}, R_{21}, R_{31})	(R_{42}, R_{51}, R_{63})	(R_{74}, R_{83}, R_{91})
RC'_6	(R_{13}, R_{21}, R_{31})	(R_{42}, R_{51}, R_{63})	(R_{72}, R_{83}, R_{91})
RC'_7	(R_{13}, R_{21}, R_{31})	(R_{42}, R_{53}, R_{63})	(R_{74}, R_{83}, R_{91})
RC'_8	(R_{13}, R_{21}, R_{31})	(R_{42}, R_{53}, R_{63})	(R_{72}, R_{83}, R_{91})

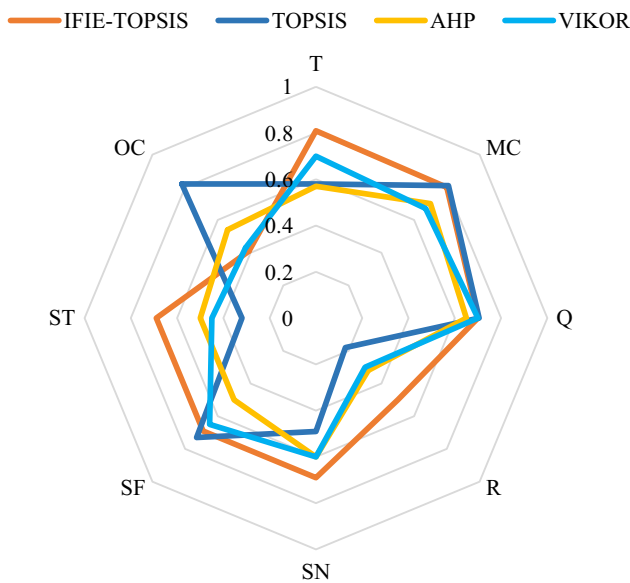


Fig. 5 Comparing of MRA schemes between IFIE-TOPSIS, TOPSIS, AHP and VIKOR

Figure 5 illustrates the comparison of the ranked #1 resources combination schemes RC_1 and RC'_7 , respectively, ranked by the proposed IFIE-TOPSIS and the traditional TOPSIS. Note that criteria T , MC and OC are cost criteria, while the other criteria are beneficial criteria. In our comparison test, linguistic value $LDi-RC'_7$ are employed to express the standard comparison value of RC'_7 of beneficial criteria. Membership degree u_{iRC1} are employed to express the standard comparison value of RC_1 of beneficial criteria. The value $(1-LDi-RC'_7)$ are employed to express the standard comparison value of RC'_7 of cost criteria. The values $(1-u_{iRC1})$ are employed to express the standard comparison value of RC_1 of cost criteria. Therefore, all criteria can be considered as beneficial criteria in comparison test, which means that the approach for the larger area of the graph enclosed by the optimal resources combination scheme in Fig. 5 is a better evaluation approach. The area of the graph

in Fig. 5 enclosed by the IFIE-TOPSIS is 1.23, enclosed by TOPSIS is 0.91, enclosed by AHP is 0.84, enclosed by VIKOR is 0.89. That means the proposed IFIE-TOPSIS is more suitable than TOPSIS, AHP and VIKOR for evaluation of MRA&CoPS in the proposed model.

Sensitivity analysis

Sensitivity analysis is a technique to observe the affection of change from some parameters of model on other elements [51]. The evaluation data of each resources in Table 7, Tables 18 and 19 are crisp number provided by resource suppliers, while the data usually are fluctuation. Data of a certain resource usually fluctuate near the corresponding area evaluated in “Evaluation process of three-layer-criteria cumulative model”. In this condition, there is a motivation to conduct a sensitivity analysis to obtain the ranking under different values of each criterion in the final product layer in terms of the traditional TOPSIS and the proposed IFIE-TOPSIS. For each criterion, seven different sets of tests of each criterion of RC_1 to RC_8 for IFIE-TOPSIS sensitivity analysis and seven different set of linguistic value of RC'_1 to RC'_8 of each criterion for TOPSIS sensitivity analysis are calculated, while data of other criteria are constant as evaluated in “Evaluation process of three-layer criteria cumulative model” and “IFIE-TOPSIS compared with the traditional TOPSIS”. Note that the sum of corresponding change value of RC_1 to RC_8 for tests 2 ~ 7 of each criterion is $-15%$, $-10%$, $-5%$, $5%$, $10%$ and $15%$ of the expected interval of the tested criterion in product layer. In addition, the sum is randomly assigned to RC_1 to RC_8 in each test. Test 1 for each criterion is the ranking result calculated in “Evaluation process of three-layer criteria cumulative model”. The test value configuration principle of RC'_1 to RC'_8 for traditional TOPSIS is same as RC_1 to RC_8 for IFIE-TOPSIS.

Figure 6 depicts the change in ranking of MRA schemes calculated by the TOPSIS and the proposed IFIE-TOPSIS in product layer. The most frequent ranked #1 RC' of each criterion and the percentage of the ranked #1 times of the most frequent ranked #1 RC' to test times of each criterion for traditional TOPSIS and IFIE-TOPSIS can be found in Table 14. For the TOPSIS approach, changing the linguistic value of each criterion significantly changes the calculated MRA scheme ranking from test to test. The percentage of the test of criterion T , Q , R , SN and SF for traditional TOPSIS are all only 43%, while the percentage of the test of the same criteria for IFIE-TOPSIS are 86%, 100%, 100%, 86% and 86%. For the proposed IFIE-TOPSIS approach, it is clear that the results are not sensitive to the changes of fuzzy value of each criterion. As Table 14 shows, RC_1 is always the most frequent ranked #1 RC of the tests for each criterion, while RC'_4 , RC'_7 and RC'_8 are the most frequent ranked #1 RC' of tests of different criterion. Further, RC_1 ranked #1 in all the seven tests

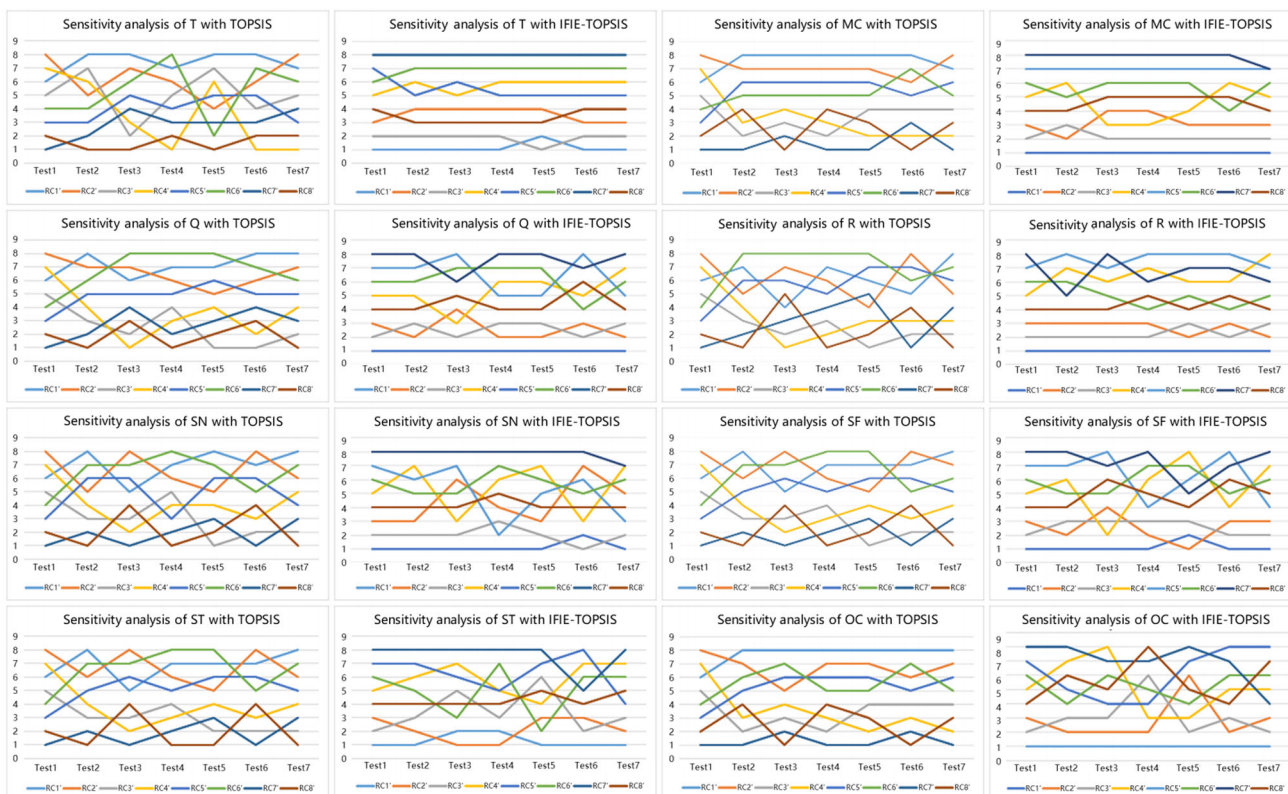


Fig. 6 Sensitivity analysis with respect to different criterion TOPSIS and IFIE-TOPSIS

Table 14 Frequency of ranked #1 resources combination schemes for TOPSIS and IFIE-TOPSIS

	Criterion	T	MC	Q	R	SN	SF	ST	OC
TOPSIS	RC' ranked #1 most times	RC'4 and RC'8	RC'7	RC'8	RC'8	RC'7 and RC'8	RC'7 and RC'8	RC'8	RC'7
	Ranked #1 times (percentage)	3 (43%)	5 (71%)	3 (43%)	3 (43%)	3 (43%)	3 (43%)	4 (57%)	4 (57%)
IFIE-TOPSIS	RC ranked #1 most times	RC ₁	RC ₁	RC ₁	RC ₁	RC ₁	RC ₁	RC ₁	RC ₁
	Ranked #1 times (percentage)	6 (86%)	7 (100%)	7 (100%)	7 (100%)	6 (86%)	6 (86%)	5 (71%)	7(100%)

of criterion *MC*, *Q*, *R* and *OC*. Figure 6 and Table 14 illustrate the ranking changes for the TOPSIS and the IFIE-TOPSIS in their test, and they clearly prove the IFIE-TOPSIS approach is more robust than the TOPSIS with respect to the possible statistical error of data of each criterion.

Conclusion

MRA is essential in manufacturing resources decision-making of CoPS. However, the complex structure, long lifecycle and combined explosion, as well as incompleteness

and fluctuation of decision information often resulted in the manufacturing resources decision-making a challenging task. It is highly desired to obtain MRA schemes, in terms of trade-off among CoPS’s manufacturing, operation and maintenance from the viewpoint of CoPS’s lifecycle. In this investigation, a MCDM model for MRA&CoPS is proposed with considering lifecycle-oriented 8-tuple evaluation criteria via three-layer accumulation. In addition, a hybrid IFIE-TOPSIS method by combining information entropy and TOPSIS has been extended in intuitionistic fuzzy environment to deal with the proposed MRA&CoPS model. The model is demonstrated with an example in a complex

cement equipment manufacture company. Simulation results and sensitivity analysis have shown the effectiveness and superiority of proposed IFIE-TOPSIS method over classical TOPSIS.

MRA decision-making is increasingly becoming an integral component of the fully functioning expert and intelligent systems with applications across various manufacturing systems, especially for CoPS. Among various MRA models, the proposed MRA&CoPS model pays attention to MRA of CoPS with the viewpoint of trade-off among manufacturing, operation and maintenance of CoPS's lifecycle. The proposed mathematical model can be categorized as a straight fuzzy MCDM (FMCDM) strategy according to the manufacturing resources evaluation framework. As a result, various alternatives of manufacturing resources should be identified to support different processes, components and products for a CoPS. In practice, medium-/long-term contracts should be made with the selected groups of manufacturing resources suppliers for the stable cooperation.

In the aspect concerning the limitations of this paper, it is important to notice that the 8-tuple evaluation criteria performance is possibly changed dynamically. Further, the proposed method stands in the view of manufacturers, whereas the CoPS's lifecycle involves other parts, such as supplier, designer and costumer. Mover, the selected optimal MRA is a constant result for CoPS, while some manufacturing resources may change over time, such as the workers' and production facilities' productivity. Concerning the limitations of this method proposed in previous, the suggestions for further research are listed as follows.

- (1) Adding time variable in the accumulation of indices according to the change value of resources to adjust the timeliness of evaluation.
- (2) Making decision for MRA&CoPS with game perspective among multiple participants, such as supplier, designer and costumer.
- (3) Considering the change of some manufacturing resources such as the productivity of workers and production facilities and constructing a risking model for the MRA evaluated by the proposed method in previous section.

Acknowledgements This research was supported by the National Natural Science Foundation of China under Project (No. 51705386).

Data availability Data is available upon request.

Declarations

Conflict of interest On behalf of all the authors, the corresponding author states that there is no conflict of interest. On behalf of all the authors, the corresponding author states that there is no financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

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Appendices (see Tables 15, 16, 17, 18, 19 and 20).

Table 15 Normalization fuzzy decision matrix in process layer of the case component

Criteria	Process 1				Process 2				Process 3			
	R_{11}	R_{12}	R_{13}	R_{14}	R_{21}	R_{22}	R_{23}	R_{24}	R_{31}	R_{32}	R_{33}	R_{34}
<i>T</i>	(0.6, 0.3)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.6, 0.3)	(0.6,0.3)	(0.8,0.1)
<i>MC</i>	(0.8, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.4)	(0.8, 0.1)	(0.5, 0.4)	(0.5, 0.4)	(0.5, 0.4)	(0.5,0.4)	(0.6,0.3)
<i>Q</i>	(0.6, 0.3)	(0.7, 0.2)	(0.5, 0.4)	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.4)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.5,0.4)	(0.6,0.3)
<i>R</i>	(0.5, 0.4)	(0.7, 0.2)	(0.6, 0.3)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.4)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.2)	(0.7, 0.2)
<i>SN</i>	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.4)	(0.7, 0.2)	(0.5, 0.4)	(0.6, 0.3)	(0.6, 0.3)	(0.5, 0.4)	(0.8, 0.1)
<i>SF</i>	(0.7, 0.2)	(0.5, 0.4)	(0.5, 0.4)	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.5, 0.4)	(0.5, 0.4)	(0.5, 0.4)	(0.6, 0.3)	(0.5, 0.4)
<i>ST</i>	(0.7, 0.2)	(0.6, 0.3)	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.7, 0.2)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)

Table 16 Normalization fuzzy decision matrix in component layer of the case component

Resources combinations	(R_{13}, R_{21}, R_{34})	(R_{13}, R_{21}, R_{32})	(R_{13}, R_{24}, R_{34})	(R_{13}, R_{24}, R_{32})	(R_{14}, R_{21}, R_{34})	(R_{14}, R_{21}, R_{32})	(R_{14}, R_{24}, R_{34})	(R_{14}, R_{24}, R_{32})
<i>T</i>	(0.7, 0.2)	(0.5, 0.4)	(0.6, 0.3)	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)
<i>MC</i>	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)
<i>Q</i>	(0.7, 0.2)	(0.5, 0.4)	(0.8, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)	(0.8, 0.1)
<i>R</i>	(0.7, 0.2)	(0.5, 0.4)	(0.7, 0.2)	(0.5, 0.4)	(0.7, 0.2)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)
<i>SN</i>	(0.7, 0.2)	(0.6, 0.3)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.4)	(0.8, 0.1)
<i>SF</i>	(0.5, 0.4)	(0.6, 0.3)	(0.6, 0.3)	(0.7, 0.2)	(0.6, 0.3)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)
<i>ST</i>	(0.7, 0.2)	(0.5, 0.4)	(0.5, 0.4)	(0.6, 0.3)	(0.7, 0.2)	(0.8, 0.1)	(0.6, 0.3)	(0.7, 0.2)

Table 17 Normalization fuzzy decision matrix in product layer

Resources combinations	RC_1	RC_2	RC_3	RC_4	RC_5	RC_6	RC_7	RC_8
<i>T</i>	(0.8, 0.1)	(0.6, 0.3)	(0.7, 0.2)	(0.7, 0.2)	(0.8, 0.1)	(0.6, 0.3)	(0.7, 0.2)	(0.5, 0.4)
<i>MC</i>	(0.5, 0.4)	(0.6, 0.3)	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.5, 0.4)
<i>Q</i>	(0.5, 0.4)	(0.6, 0.3)	(0.7, 0.2)	(0.6, 0.3)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)	(0.6, 0.3)
<i>R</i>	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)
<i>SN</i>	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.3)	(0.7, 0.2)	(0.5, 0.4)	(0.5, 0.4)
<i>SF</i>	(0.5, 0.4)	(0.8, 0.1)	(0.6, 0.3)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.4)	(0.6, 0.3)
<i>OC</i>	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.4)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.2)
<i>ST</i>	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.3)	(0.5, 0.4)	(0.8, 0.1)	(0.5, 0.4)	(0.8, 0.1)

Table 18 The manufacturing data of the criteria for hydraulic lift

	Process 1				Process 2				Process 3			
	R_{41}	R_{42}	R_{43}	R_{44}	R_{51}	R_{52}	R_{53}	R_{54}	R_{61}	R_{62}	R_{63}	R_{64}
<i>T (h)</i>	6.3	9.1	5.5	9.2	5.6	9.2	9.8	5.6	9.6	6.1	6.2	9.4
<i>MC (¥)</i>	216.5	218	202	204.5	202.5	204.5	216	202	203.5	203	203	205.5
<i>Q</i>	0.96	0.975	0.955	0.97	0.96	0.955	0.995	0.975	0.995	0.99	0.955	0.96
<i>R</i>	0.915	0.94	0.925	0.99	0.94	0.925	0.915	0.96	0.97	0.925	0.94	0.95
<i>SN</i>	0.75	0.94	0.96	0.7	0.65	0.65	0.78	0.67	0.69	0.7	0.66	0.98
<i>SF</i>	0.97	0.955	0.955	0.965	0.995	0.995	0.975	0.955	0.955	0.955	0.96	0.955
<i>ST</i>	0.85	0.81	0.96	0.9	0.9	0.9	0.96	0.85	0.82	0.81	0.95	0.97

Table 19 The manufacturing data of the criteria for hydraulic lift

	Process 7				Process 8				Process 9			
	R_{71}	R_{72}	R_{73}	R_{74}	R_{81}	R_{82}	R_{83}	R_{84}	R_{91}	R_{92}	R_{93}	R_{94}
T (h)	9.1	6.3	5.3	6.4	6.2	9.3	6.3	5.7	9.1	8	5.6	8.8
MC (¥)	205	217	215	217	207	204	213	214.5	215	204	216	212
Q	0.99	0.965	0.96	0.965	0.935	0.93	0.96	0.93	0.995	0.94	0.965	0.96
R	0.945	0.925	0.92	0.925	0.96	0.98	0.915	0.965	0.955	0.98	0.875	0.95
SN	0.75	0.65	0.8	0.7	0.65	0.74	0.7	0.7	0.7	0.65	0.7	0.55
SF	0.94	0.985	0.97	0.985	0.975	0.965	0.995	0.99	0.965	0.965	0.99	0.96
ST	0.95	0.95	0.82	0.95	0.95	0.81	0.83	0.9	0.6	0.95	0.8	0.84

Table 20 Normalization crisp decision matrix in product dimension for TOPSIS

Scheme	RC'_1	RC'_2	RC'_3	RC'_4	RC'_5	RC'_6	RC'_7	RC'_8
T	0.50	0.49	0.68	0.67	0.25	0.25	0.43	0.43
MC	0.94	0.94	0.38	0.38	0.84	0.84	0.28	0.28
Q	0.75	0.75	0.73	0.73	0.74	0.74	0.72	0.72
R	0.40	0.40	0.56	0.56	0.01	0.01	0.16	0.16
SN	0.45	0.42	0.31	0.28	0.63	0.59	0.49	0.45
SF	0.77	0.77	0.75	0.75	0.76	0.76	0.74	0.74
OC	0.41	0.16	0.26	0.25	0.18	0.25	0.16	0.24
ST	0.4	0.48	0.32	0.56	0.4	0.48	0.24	0.4

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