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Manufacturing Process Innovation-Oriented Knowledge Evaluation Using MCDM and Fuzzy Linguistic Computing in an Open Innovation Environment

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Abstract: In today's complex, constantly evolving and innovation-supporting manufacturing systems, knowledge plays a vital role in sustainable manufacturing process planning and problem-solving, especially in the case of Computer-Aided Process Innovation (CAPI). To obtain formalized and promising process innovation knowledge under the open innovation paradigm, it is necessary to evaluate candidate knowledge and encourage improvement suggestions based on actual innovation situations. This paper proposes a process innovation-oriented knowledge evaluation approach using Multi-Criteria Decision-Making (MCDM) and fuzzy linguistic computing. Firstly, a comprehensive hierarchy evaluation index system for process innovation knowledge is designed. Secondly, by combining an analytic hierarchy process with fuzzy linguistic computing, a comprehensive criteria weighting determination method is applied to effectively aggregate the evaluation of criteria weights for each criterion and corresponding sub-criteria. Furthermore, fuzzy linguistic evaluations of performance ratings for each criterion and corresponding sub-criteria are calculated. Thus, a process innovation knowledge comprehensive value can be determined. Finally, an illustrative example of knowledge capture, evaluation and knowledge-inspired process problem solving for micro-turbine machining is presented to demonstrate the applicability of the proposed approach. It is expected that our model would lay the foundation for knowledge-driven CAPI in sustainable manufacturing.

Keywords: manufacturing process innovation; computer-aided innovation; CAPI; knowledge management; open innovation; multi-criteria decision-making

1. Introduction

During the past decades, the structure of the world economy has undergone significant changes with demand for energy saving and environmental protection becoming increasingly urgent [1–3]. To cope with this situation, developing countries need to transform and upgrade their

manufacturing industries with process innovation to reduce energy consumption and achieve sustainable development; developed countries, accordingly, are trying to guide and accelerate the return of manufacturing industries for enhancing global competitive advantage by means of process innovation [4–7]. Manufacturing process innovation, which includes the creation of new technical principles, methods and production modes, is a basic guarantee for the ultimate realization of product innovation and a fundamental means to achieve sustainable development of the manufacturing industry [8,9]. In recent years, systematic innovation methodologies and technologies for manufacturing processes have gained greater attention in academic research and industry [10–12]. Nevertheless, process innovation typically relies on cross-industry collaboration and potentially complex interdisciplinary system engineering [9]; thus, in addition to sophisticated manufacturing environments, the delivery of innovation is more dependent on highly qualified knowledge and knowledge-based systematic innovation methods [13–17]. Consequently, formalized process innovation-oriented knowledge acquisition and its management are becoming increasingly important and challenging for knowledge intensive manufacturing industries, such as aviation, aerospace and automotive sector.

The latest Web 2.0 technologies provide a technical means for open knowledge management, enabling large amounts of discrete knowledge to be shared in open environments [18,19], such as social wiki platforms. From the perspective of knowledge application in Computer-Aided Process Innovation (CAPI) [9], a formalized knowledge-oriented systematic design process is a prerequisite and basis for innovation implementation. Therefore, it is necessary to establish an effective knowledge evaluation method in open innovation environments. Process innovation knowledge evaluation is needed to identify the validity and novelty of such knowledge and to further analyze and understand the potential practicability and profitability in current manufacturing processes by considering the knowledge characteristics and manufacturing capacity. To select process innovation-oriented candidate knowledge, a reasonable evaluation index system is required. A quantitative index and qualitative factors based on the evaluation criteria can be evaluated by multiple domain experts. Accordingly, process innovation knowledge evaluation should be regarded as a group Multi-Criteria Decision-Making (MCDM) problem [20,21], concerned with how to evaluate candidate knowledge and how to raise improvement suggestions.

Due to the complexity and fuzziness of the above problems, it is difficult for decision makers to evaluate given objects using exact values, but they can express preferences using fuzzy linguistic values [22,23]. Experts devote themselves to judging knowledge comprehensive values by subjective perception or experiential cognition during the decision-making process. However, there exists a certain extent of fuzziness, uncertainty and heterogeneity [24,25]. In addition, there is a tendency towards information loss during integration processes and this can cause the evaluation results of knowledge performance levels to be inconsistent with the expectation of experts [26,27]. In this event, there is a need to identify reasonable ways of calculating the performance ratings of process innovation-oriented knowledge during the process of evaluation integration.

Therefore, the main objective of this research is to develop a comprehensive knowledge evaluation approach for supporting knowledge-driven CAPI. Firstly, an evaluation index system for process innovation knowledge is designed by domain experts, and necessary data from the expert committee are gathered to determine criteria weightings and performance ratings of candidate knowledge. Then, by combining an Analytic Hierarchy Process (AHP) with fuzzy linguistic computing, a comprehensive criteria weighting determination method for the knowledge evaluation index system is explored. What follows is the fuzzy linguistic evaluation of the performance ratings for each criterion and the corresponding sub-criteria can be calculated. Furthermore, it is possible to compute the process innovation-oriented knowledge comprehensive value and propose improvement suggestions based on the evaluation results.

The rest of this paper is organized as follows. In Section 2, background research and related work with definitions are introduced, while operations relating to 2-tuple fuzzy linguistic variable are explored. In Section 3, we introduce the comprehensive evaluation index system for process innovation knowledge, the model and procedure for process innovation-oriented knowledge

evaluation, and the determination of comprehensive fuzzy weights. Then, a real case study of process innovation knowledge capture and evaluation for micro-cutting is illustrated in Section 4 and further studied, with a process problem solving example of a micro-turbine manufacturing issue being given. Finally, conclusions and future directions for research are discussed.

2. Related Work and Preliminaries

2.1. Knowledge-Driven Computer-Aided Process Innovation

The concept of process innovation was first proposed by Schumpeter [8] from the perspective of economic development and, soon after, received attention in both academic research and industry, especially in the context of energy saving and environmental protection [28,29]. In recent years, some scholars have carried out useful explorations into specific types manufacturing process innovation by using the Theory of Inventive Problem Solving (Russian acronym: TRIZ) and knowledge engineering [11,30–32]. With the development of Computer-Aided Innovation (CAI) technology and the requirements of manufacturing process problem-solving [33], the concept of computer-aided process innovation was advanced, with some specific application cases being used to illustrate the feasibility of structured/systematic process innovation design [9,12,34–36]. In fact, the traditional computer aided methods of manufacturing process (e.g., Computer-Aided Process Planning (CAPP) and Computer-Aided Manufacturing (CAM)) are mainly used for improving the efficiency and standardization of process planning [37,38], while CAPI is more focused on solving manufacturing process problems, improving process methodologies, fostering whole process innovation design cycles and even enhancing the overall manufacturing innovation capability of enterprises.

As is commonly recognized, knowledge is an essential asset for organizations and plays a crucial role in innovation; innovation can be regarded as the knowledge-based creation, and the knowledge-based outcome [13,39,40]. Process innovation knowledge is used to support process innovation activities correctly implemented and to produce new process knowledge. Obviously, the knowledge acquisition and management of CAPI is crucial to innovative design, especially in the context of open innovation. Hüsig and Kohn [18] introduced the "Open CAI 2.0" concept based on analysis of open innovation strategy and Web 2.0 technologies. By combining the technical characteristics of social networks with wiki technology, Wang et al. [9] proposed a novel process innovation knowledge accumulation schema based on bilayer social wiki network for CAPI.

In social wiki networks for CAPI, process innovation knowledge could be accumulated in a public knowledge space through participants' social interactions and knowledge activities, however, this generated knowledge may not be able to meet actual requirements—it still needs to be evaluated and optimized through reasonable means to ensure the quality of knowledge and support for knowledge-inspired innovation design, as shown in Figure 1. Hence, it is necessary to establish an evaluation index system for process innovation knowledge and to provide evaluation results and suggestions for improvement based on the evaluation information from expert groups. In this study, we will focus on knowledge evaluation for CAPI in an open-innovation environment.

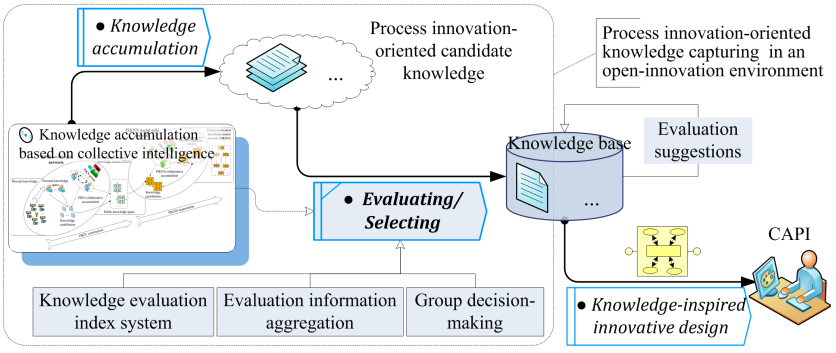

Figure 1. Process innovation-oriented knowledge evaluation in an open innovation environment.

2.2. Definition and Computing of the Fuzzy Linguistic Method

In group decision making for knowledge evaluation, decision makers usually apply fuzzy linguistic evaluation based on subjective experiences due to the complexity of process innovation and decision making. In fuzzy linguistic approach, two traditional computational models can be identified: (1) a linguistic computing model based on membership functions [41]; and (2) a symbolic linguistic computing model which produces loss of information due to approximation processes and hence produces a lack of precision in results [42]. To avoid information loss and to improve computational precision, Herrera and Martínez [26] proposed the 2-tuple fuzzy linguistic representation model. It not only inherits the existing advantage of fuzzy linguistic computing, but also overcomes the disadvantage of information loss experienced by other methods.

The 2-tuple linguistic computational model provides accurate and understandable results because they are represented by means of a linguistic term and a numerical value. A 2-tuple linguistic variable can be denoted as (s_i, α_i), where s_i represents the central value of the ith linguistic term, and α_i denotes the distance to the central value of the ith linguistic term. A 2-tuple linguistic variable set typically comprises three, five, seven or more terms. Usually, a five-term set has more practical applications [22]. Basic definitions and concepts of fuzzy linguistic variables are briefly given as follows.

Definition 1. *Let* $S = \{s_0, s_1, ..., s_g\}$ *be a linguistic term set, and* $\beta \in [0,1]$ *be a number value representing the aggregation result of linguistic symbolic. Then, the generalized translation function (*Δ*) applied to translate* β *into a 2-tuple linguistic variable is defined as*

$$\Delta : [0,1] \to S \times \left[-\frac{1}{2g}, \frac{1}{2g} \right) ,$$
$$\Delta(\beta) = (s_i, \alpha) = \begin{cases} s_i, & i = round(\beta \cdot g) \\ \alpha = \beta - \frac{i}{g}, & \alpha \in \left[-1/2g, 1/2g \right) \end{cases} , \quad (1)$$

where $round(\cdot)$ is the usual round operation, s_i has the closest attribute label to β, and α is the value of the symbolic translation.

Definition 2. *On the contrary, a reverse equation* Δ^{-1} *is necessary to convert the 2-tuple linguistic variable into its equivalent value* $\beta \in [0,1]$*, which can be computed by the following formula*

$$\Delta^{-1}(s_i, \alpha) = \beta = \alpha + \frac{i}{g} . \quad (2)$$

Definition 3. *Let* $S = \{(s_1, \alpha_1), ..., (s_n, \alpha_n)\}$ *be a set of 2-tuple fuzzy linguistic variable, where their arithmetic mean* $\overline{S}$ *is calculated as*

$$\overline{S} = \Delta\left(\frac{1}{n} \sum_{i=1}^{n} \Delta^{-1}(s_i, \alpha_i) \right) = \Delta\left(\frac{1}{n} \sum_{i=1}^{n} \beta_i \right) = (s_t, \alpha_t)$$
$$s_t \in S, \ \alpha_t \in \left[-1/2g, 1/2g \right) \quad (3)$$

Definition 4. *Let* $S = \{(s_1, \alpha_1), ..., (s_n, \alpha_n)\}$ *be a 2-tuple fuzzy linguistic variable set, and* $W = \{w_1, ..., w_n\}$ *be the weight set of linguistic terms; their 2-tuple linguistic weighted average* $\overline{S}^w$ *is calculated as*

$$\overline{S}^{w} = \Delta\left(\frac{\sum_{i=1}^{n}\Delta^{-1}(s_i,\alpha_i)\cdot w_i}{\sum_{i=1}^{n} w_i}\right) = \Delta\left(\frac{\sum_{i=1}^{n}\Delta^{-1}(\beta_i \cdot w_i)}{\sum_{i=1}^{n} w_i}\right) = \left(s^{w},\alpha^{w}\right), \quad s^{w} \in S,\ \alpha^{w} \in \left[-1/2g,\ 1/2g\right) \tag{4}$$

Additionally, when $W = \{(w_1,\alpha_{w1}),...,(w_n,\alpha_{wn})\}$ is the linguistic weight set of each s_i, this linguistic weighted average operator can be computed as

$$\overline{S}_{l}^{w} = \Delta\left(\frac{\sum_{i=1}^{n}\left[\Delta^{-1}(s_i,\alpha_i)\cdot\Delta^{-1}(w_i,\alpha_{wi})\right]}{\sum_{i=1}^{n}\Delta^{-1}(w_i,\alpha_{wi})}\right). \tag{5}$$

Definition 5. *Let* (s_i,α_i) *and* (s_j,α_j) *be two 2-tuple fuzzy linguistic variables, where the comparison of both linguistic variables can be shown as:*

(a) *If* $i < j$, *then* (s_i,α_i) *is worse than* (s_j,α_j).

(b) *If* $i = j$ *and* $\alpha_i = \alpha_j$, *then* (s_i,α_i) *is equal to* (s_j,α_j).

(c) *If* $i = j$ *and* $\alpha_i > \alpha_j$, *then* (s_i,α_i) *is better than* (s_j,α_j).

(d) *If* $i = j$ *and* $\alpha_i < \alpha_j$, *then* (s_i,α_i) *is worse than* (s_j,α_j).

3. The Proposed Approach

3.1. Proposed Comprehensive Evaluation Index System for Process Innovation Knowledge

Knowledge evaluation is an important part of process innovation knowledge acquisition, which requires not only an effective evaluation method, but also a practical index system as the basis for evaluation. The selection of a knowledge evaluation index depends on the specific application environment and innovation objects, thus reasonable control of the size and flexibility of the index system is necessary. In this research, through a review of literature and discussion with domain experts, we present a comprehensive hierarchy evaluation index system for process innovation knowledge, as illustrated in Figure 2. The evaluation index system is composed of three levels: the first level is the overall goal; the second level comprises evaluation criteria; and the third level denotes corresponding sub-criteria for each criterion. The goal layer represents the core value of knowledge in the innovative application scenario, named Process Innovation Knowledge Comprehensive Value (PIKCV). The PIKCV is then divided into four parts through analysis of the characteristics of manufacturing process innovation: knowledge validity, knowledge novelty, potential practicability and manufacturing profitability.

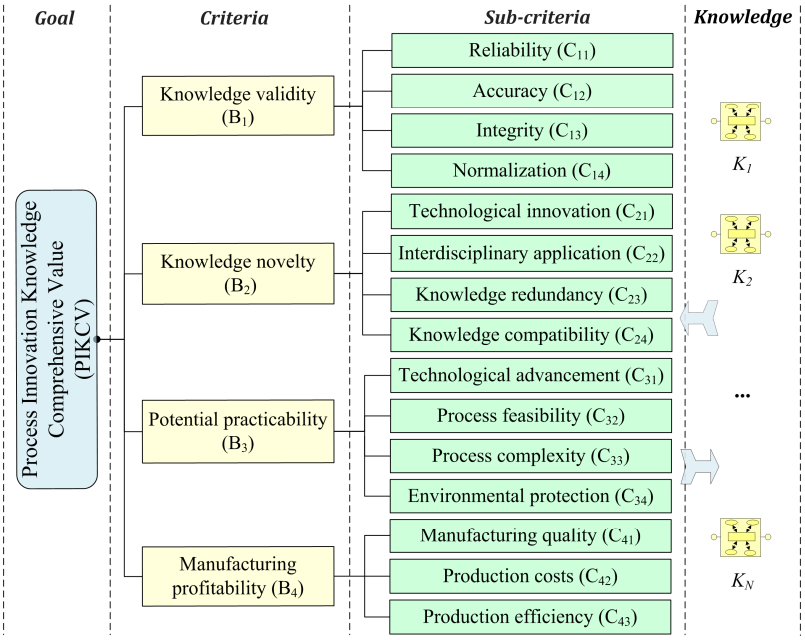

Figure 2. The proposed comprehensive evaluation index system for process innovation knowledge.

3.2. Process Innovation-Oriented Knowledge Evaluation Model

In an open knowledge acquisition context, candidate innovation knowledge generally includes new theories, new methods and/or practical examples. Due to the novelty of knowledge and the complexity of process problems, it is difficult to fully evaluate the value of candidate process innovation knowledge from multiple criteria using exact values. In this situation, fuzzy linguistic variables are considered more reasonable for domain experts to evaluate the performance of PIKCV. Consequently, based on analysis of the comprehensive evaluation index system, a suitable evaluation model, using fuzzy linguistic computing, is proposed to measure the level of process innovation-oriented knowledge, as represented in Figure 3. The specific procedures of this proposed evaluation model are summarized as follows.

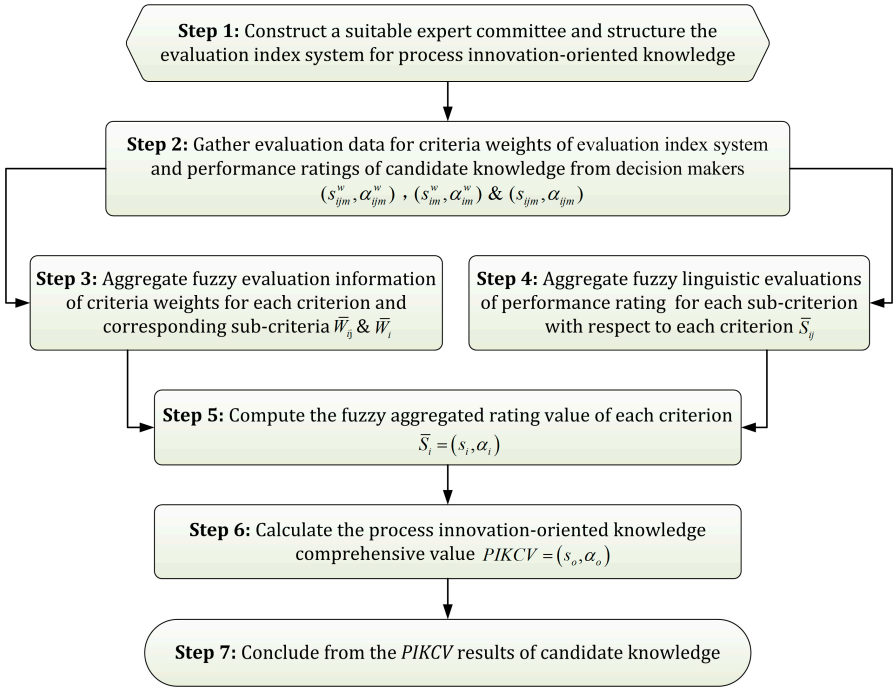

Figure 3. The procedure of manufacturing process innovation-oriented knowledge evaluation.

Step 1. Form a suitable expert committee with members who are familiar with manufacturing process innovation design and the structure of the evaluation index system for the corresponding innovation knowledge. Let $E=\{E_1,E_2,...,E_M\}$ be the established expert committee and $K=\{K_1,K_2,...,K_N\}$ be a set of candidate process innovation knowledge. Additionally, assume that there are n criteria $B_i\,(i=1,2,...,n)$, and each criterion includes several sub-criteria $C_{ij}\,(i=1,2,...,n;\ j=1,2,...,t)$ in the evaluation index system for process innovation knowledge.

Step 2. Select appropriate granularity for the linguistic term set according to experience and the preference of decision makers, and gather necessary data containing criteria weights and the performance ratings from the expert committee. Transform these linguistic terms into 2-tuple linguistic variables; for example, $(s_{ijm}^w,\alpha_{ijm}^w)$ can denote the 2-tuple fuzzy criteria weights of the *j*th sub-criteria regarding the *i*th criteria of the *m*th expert.

Step 3. Aggregate the fuzzy linguistic evaluations of criteria weights generated by the expert committee for each criterion and corresponding sub-criteria. According to the arithmetic mean Formula (3), the aggregated criteria weighting values of *M* experts are calculated as follows:

$$\bar{W}_{ij}=\Delta\left(\sum_{m=1}^{M}\left[\Delta^{-1}(s_{ijm}^w,\alpha_{ijm}^w)\cdot w_m^E\right]\right)=\Delta\left(\sum_{m=1}^{M}\left[\beta_{ijm}^w\cdot w_m^E\right]\right)=\left(s_{ij}^w,\alpha_{ij}^w\right), \tag{6}$$

$$\bar{W}_{i}=\Delta\left(\sum_{m=1}^{M}\left[\Delta^{-1}(s_{im}^w,\alpha_{im}^w)\cdot w_m^E\right]\right)=\Delta\left(\sum_{m=1}^{M}\left[\beta_{im}^w\cdot w_m^E\right]\right)=\left(s_{i}^w,\alpha_{i}^w\right), \tag{7}$$

where s_{ijm}^w is the fuzzy importance of sub-criteria j with respect to B_i of the m th expert, s_{im}^w is the fuzzy importance of B_i of the m th expert, and $w_m^E\in[0,1]$ is the expert weight of the m th expert in determination of criteria importance, $\sum_{m=1}^{M}w_m^E=1$.

In particular, when the expert weights are equal to each other, the aggregated criteria weighting values can be obtained using Formula (3):

$$\bar{W}_{ij}=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\Delta^{-1}(s_{ijm}^w,\alpha_{ijm}^w)\right)=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\beta_{ijm}^w\right)=\left(s_{ij}^w,\alpha_{ij}^w\right), \tag{8}$$

$$\bar{W}_{i}=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\Delta^{-1}(s_{im}^w,\alpha_{im}^w)\right)=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\beta_{im}^w\right)=\left(s_{i}^w,\alpha_{i}^w\right), \tag{9}$$

Step 4. Aggregate the fuzzy linguistic evaluations of performance rating for each sub-criterion with respect to each criterion. Assuming that expert weights are the same in performance evaluation of process innovation knowledge, we can obtain the aggregation of fuzzy linguistic evaluation values.

$$\bar{S}_{ij}=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\Delta^{-1}(s_{ijm},\alpha_{ijm})\right)=\Delta\left(\frac{1}{M}\sum_{m=1}^{M}\beta_{ijm}\right)=\left(s_{ij},\alpha_{ij}\right), \tag{10}$$

where s_{ijm} is the fuzzy rating of sub-criteria j with respect to B_i of the m th expert.

Step 5. Compute the fuzzy aggregated ratings of each criterion by applying Formula (4):

$$\bar{S}_{i}=\Delta\left(\frac{\sum_{j=1}^{n_i}\left[\Delta^{-1}(r_{ij},\alpha_{ij})\cdot\beta_{ij}^w\right]}{\sum_{j=1}^{n_i}\beta_{ij}^w}\right)=\Delta\left(\frac{\sum_{j=1}^{n_i}\left[\left(\beta_{ij}\cdot\beta_{ij}^w\right)\right]}{\sum_{j=1}^{n_i}\beta_{ij}^w}\right)=\left(s_{i},\alpha_{i}\right), \tag{11}$$

where

$$\beta_{ij} = \Delta^{-1}(r_{ij}, \alpha_{ij}),\ \beta_{ij}^{w} = \Delta^{-1}(w_{ij}, \alpha_{ij}^{w}),\ s_i \in S,\ \alpha_i \in \left[-\frac{1}{2g}, \frac{1}{2g}\right), \tag{12}$$

Step 6. Calculate the process innovation knowledge comprehensive value. The linguistic term s_o can be used to represent the overall value level of process innovation knowledge in innovative design.

$$PIKCV = \Delta\left(\frac{\sum_{i=1}^{n}\left(\Delta^{-1}(r_i, \alpha_i)\cdot\beta_i^{w}\right)}{\sum_{i=1}^{n}\beta_i^{w}}\right) = \Delta\left(\frac{\sum_{i=1}^{n}\left(\beta_i\cdot\beta_i^{w}\right)}{\sum_{i=1}^{n}\beta_i^{w}}\right) = (s_o, \alpha_o), \tag{13}$$

where

$$\beta_i = \Delta^{-1}(r_i, \alpha_i),\ \beta_i^{w} = \Delta^{-1}(w_i, \alpha_{w_i}),\ s_o \in S,\ \alpha_o \in \left[-\frac{1}{2g}, \frac{1}{2g}\right), \tag{14}$$

Step 7. Rank the candidate knowledge based on PIKCV results, and propose improvement suggestions, according to evaluation results in the corresponding criteria and sub-criteria.

3.3. Determination of Fuzzy Comprehensive Weights

The determination of weights is crucial to fuzzy comprehensive evaluation of process innovation knowledge; however, due to the complexity of creative problem-solving and the ambiguity of human thinking, it is difficult to give a clear standard weight. In general, experts are used to determine the weights using two methods: fuzzy linguistic representation and AHP. Here, to meet the diversity requirements of the expert group in weight determination, and to ensure the reliability of the weight coefficient, we compute the comprehensive weight of the knowledge evaluation system by combining AHP with fuzzy linguistic computing.

3.3.1. Weight Coefficient of AHP

The AHP method, developed by Saaty [43] in the 1970s, is widely used for dealing with MCDM problems in practical production engineering [7,20,25,44–46]. It decomposes complex decision problems into hierarchical structures, which can include goal layer, criterion layer and sub-criterion layer. Then, a series of pairwise comparisons is conducted among the elements at the same level, so as to construct the judgment matrix. The specific steps for determination of weight coefficient are as follows:

1. A numerical rating for judgment matrix of pairwise comparison is suggested. Furthermore, a judgment matrix A is constructed according to pairwise comparisons.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \tag{15}$$

   where a_{ij} is the relative importance comparison value of element u_i to element u_j, and $a_{ij} > 0,\ a_{ji} = 1/a_{ij}$.

2. Calculate the weighted weight set W^A according to the judgment matrix by using the following formula:

$$w_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \Big/ \sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij}}, \quad W^A = \{w_1, w_2, ..., w_n\}, \tag{16}$$

3. An index, called consistency index (CI), is then used to measure the amount of inconsistency within the pairwise comparison matrix A.

$$CI = (\lambda_{max} - n) \Big/ (n-1), \tag{17}$$

where λ_{max} is the largest eigenvalue of A, calculated as follows:

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{Aw_i}{w_i}, \tag{18}$$

Accordingly, the Consistency Rate CR is used to measure the degree of CI by using the following formula:

$$CR = CI \Big/ RI, \tag{19}$$

where RI is the random consistency index, its value being dependent on the order of matrix (as listed in Table 1).

When $CR < 0.1$, the judgment matrix and weights of elements are acceptable. Otherwise, the comparison matrix must be adjusted and decision makers should be asked to re-judge.

Table 1. Random consistency index of judgment matrix.

Order of Matrix	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

3.3.2. Weight Coefficient of Fuzzy Linguistic Computing

The aggregated criteria weighting values for each criterion and corresponding sub-criteria can be obtained using Formulae (6)–(9). Then, the following formulae are used to normalize these aggregated weights:

$$w_i = \beta_i^w \Big/ \sum_{i=1}^{n} \beta_i^w, \tag{20}$$

where β_i^w is the aggregated result of i th criterion in the criterion layer and n is the number of criteria.

$$w_{ij} = \beta_{ij}^w \Big/ \sum_{j=1}^{n_i} \beta_{ij}^w, \tag{21}$$

where β_{ij}^w is the aggregated result of j th sub-criterion in the sub-criterion layer and n is the number of sub-criteria for i th criterion.

3.3.3. Fuzzy Comprehensive Weights

By considering the weight information from the expert group of AHP and fuzzy linguistic computing, we can obtain the fuzzy comprehensive weights.

$$W^C = \left(\sum_A w_m^E \right) W^A + \left(\sum_L w_m^E \right) W^L , \quad (22)$$

where W^C is the fuzzy comprehensive weight set of knowledge evaluation; W^A is the weighted weight set of the AHP expert group; W^L is the aggregated weight set of fuzzy linguistic computing; and $\sum_A w_m^E$ and $\sum_L w_m^E$ are the sums of expert weights from expert groups of AHP and fuzzy linguistic computing, respectively;

$$\sum_A w_m^E + \sum_L w_m^E = 1. \quad (23)$$

4. An Illustrative Example

To illustrate the applicability of the developed approach, a real case study of process innovation knowledge capture and evaluation for micro-cutting is presented. A contrastive analysis and discussion between the proposed method and traditional simple weight additive (SWA) method is performed. Thereafter, knowledge-inspired process problem solving for micro-turbine manufacturing is illustrated.

4.1. Process Innovation Knowledge Capturing and Evaluating

Process innovation knowledge, which exists in the entire life cycle of CAPI, is used to support process innovation activities and, if correctly implemented, produces new process knowledge. According to Wang et al. [9] and Geng et al. [12], process innovation knowledge can be divided into several types, including problem description template (PDT), process contradiction matrix (PCM), manufacturing scientific effect (MSE), innovative scheme instance (ISI), manufacturing capability description (MCD), etc. Through knowledge contributors' social wiki activities in the context of open innovation, multiple types of process innovation knowledge for micro-cutting technology have been initially accumulated. Among this knowledge, there are six solving principles of PCM that need to be evaluated for a specific innovation scenario: $\{K_1, K_2, K_3, K_4, K_5, K_6\}$. In the following section, we take principle knowledge as an example to illustrate the concrete process of innovation knowledge evaluation and selection.

4.1.1. Gathering of Evaluation Data

To gather necessary data, the researchers conducted in-depth interviews with an expert committee, the members of which include a process designer, innovation expert and technical manager and who were introduced to the linguistic variables and their semantics. The committee consisted of three experts: $\{E_1, E_2, E_3\}$. The Linguistic variables of the importance and rating are displayed in Table 2.

In determining the weights of the evaluation system, two experts (E_1, E_2) used fuzzy linguistic variables and one expert (E_3) used AHP. Linguistic evaluation and weighting values from E_1, E_2 are listed in Table 3, and the judgment matrices of criteria and sub-criteria from E_3 are shown as follows.

$$A=\begin{bmatrix} 1 & 4 & 3 & 6 \\ 1/4 & 1 & 1/3 & 3 \\ 1/3 & 3 & 1 & 5 \\ 1/6 & 1/3 & 1/5 & 1 \end{bmatrix};$$

$$A_1=\begin{bmatrix} 1 & 5 & 3 & 5 \\ 1/5 & 1 & 1/3 & 3 \\ 1/3 & 3 & 1 & 5 \\ 1/5 & 1/3 & 1/5 & 1 \end{bmatrix}, A_2=\begin{bmatrix} 1 & 6 & 6 & 4 \\ 1/6 & 1 & 1 & 1/3 \\ 1/6 & 1 & 1 & 1/3 \\ 1/4 & 3 & 3 & 1 \end{bmatrix}, \quad (24)$$

$$A_3=\begin{bmatrix} 1 & 1/6 & 1 & 3 \\ 6 & 1 & 5 & 6 \\ 1 & 1/5 & 1 & 3 \\ 1/3 & 1/6 & 1/3 & 1 \end{bmatrix}, A_4=\begin{bmatrix} 1 & 3 & 4 \\ 1/3 & 1 & 3 \\ 1/4 & 1/3 & 1 \end{bmatrix}$$

Table 2. Linguistic variable and its semantics for the importance and rating.

Linguistic Label	Linguistic Term		Triangular Fuzzy Number
	Importance	Rating	
s_0	Very unimportant (VU)	Very poor (VP)	(0, 0, 0.25)
s_1	Unimportant (U)	Poor (P)	(0, 0.25, 0.5)
s_2	Fair (F)	Fair (F)	(0.25, 0.5, 0.75)
s_3	Important (I)	Good (G)	(0.5, 0.75, 1.0)
s_4	Very important (VI)	Very good (VG)	(0.75, 1.0,1.0)

The performance ratings of sub-criteria for candidate knowledge are given in Table 4.

4.1.2. Determination of Criteria Weights

In determining the criteria weights for this study, we assume that the vector of expert weight is $[0.3, 0.3, 0.4]$ according to the experts' professional knowledge and innovation background. Thus, by using Formulae (6)–(9), the aggregated criteria weights of each criterion and corresponding sub-criteria are obtained, as shown in the rightmost column of Table 3. For example, the weights of "Reliability" and "Knowledge validity" are calculated as

$$\begin{aligned} \bar{W}_{11}^L &= \Delta\left(\frac{1}{2}\sum\left[\Delta^{-1}(s_4,0)\right],\left[\Delta^{-1}(s_4,0)\right]\right)=\Delta(1.0)=(s_4,0), \\ \bar{W}_1^L &= \Delta\left(\frac{1}{2}\sum\left[\Delta^{-1}(s_4,0)\right],\left[\Delta^{-1}(s_3,0)\right]\right)=\Delta(0.875)=(s_3,0.125) \end{aligned}, \quad (25)$$

After normalizing the aggregated weighting value in Table 3, we obtain fuzzy linguistic weights for criterion layer and sub-criterion layer.

$$\begin{aligned} &W^L=\{0.269,0.269,0.269,0.193\} \\ &W_1^L=\{0.296,0.244,0.230,0.230\},\ W_2^L=\{0.292,0.208,0.208,0.292\}, \\ &W_3^L=\{0.250,0.286,0.214,0.250\},\ W_4^L=\{0.389,0.333,0.278\} \end{aligned} \quad (26)$$

Based on the judgment matrix from Expert E_3 and Formulae (16)–(19), we can obtain the AHP weight of criterion layer $W^A = \{0.535, 0.130, 0.275, 0.060\}$, $\lambda_{max} = 4.148$, $CI = 0.049$, $RI = 0.89$, and $CR = 0.055 < 0.1$. Thus, this judgment matrix passes the consistency test. Similarly, the AHP weights of sub-criterion layer are obtained.

$$\begin{aligned} W_1^A &= \{0.540, 0.123, 0.274, 0.063\},\ W_2^A = \{0.612, 0.086, 0.086, 0.216\}, \\ W_3^A &= \{0.146, 0.637, 0.153, 0.064\},\ W_4^A = \{0.614, 0.268, 0.118\} \end{aligned} \tag{27}$$

When the above steps are completed, the fuzzy comprehensive weight of the criterion layer can be calculated according to Formula (22), namely $W^C = \{0.375, 0.213, 0.271, 0.141\}$. Similarly, we can obtain the fuzzy comprehensive weights of sub-criterion layer.

$$\begin{aligned} W_1^C &= \{0.393, 0.196, 0.248, 0.163\},\ W_2^C = \{0.420, 0.160, 0.160, 0.260\}, \\ W_3^C &= \{0.208, 0.426, 0.190, 0.176\},\ W_4^C = \{0.479, 0.307, 0.214\} \end{aligned} \tag{28}$$

Table 3. Linguistic evaluation and weighting value of importance of each criterion and corresponding sub-criteria.

Criteria	Sub-Criteria	Importance		Aggregated Weighting Value
		E_1	E_2	
Knowledge validity (B_1)		I	VI	$(s_3, 0.125)$
	Reliability (C_{11})	VI	VI	$(s_4, 0)$
	Accuracy (C_{12})	I	VI	$(s_3, 0.125)$
	Integrity (C_{13})	I	I	$(s_3, 0)$
	Normalization (C_{14})	F	VI	$(s_3, 0)$
Knowledge novelty (B_2)		I	VI	$(s_3, 0.125)$
	Technological innovation (C_{21})	I	VI	$(s_3, 0.125)$
	Interdisciplinary application (C_{22})	F	I	$(s_3, -0.125)$
	Knowledge redundancy (C_{23})	I	F	$(s_3, -0.125)$
	Knowledge compatibility (C_{24})	I	VI	$(s_3, 0.125)$
Potential practicability (B_3)		VI	I	$(s_3, 0.125)$
	Technological advancement (C_{31})	I	VI	$(s_3, 0.125)$
	Process feasibility (C_{32})	VI	VI	$(s_4, 0)$
	Process complexity (C_{33})	I	I	$(s_3, 0)$
	Environmental protection (C_{34})	I	VI	$(s_3, 0.125)$
Manufacturing profitability (B_4)		F	I	$(s_3, -0.125)$
	Manufacturing quality (C_{41})	VI	I	$(s_3, 0.125)$
	Production costs (C_{42})	I	I	$(s_3, 0)$
	Production efficiency (C_{43})	I	F	$(s_3, -0.125)$

Table 4. Performance ratings of sub-criteria for candidate knowledge.

Candidate Knowledge		Performance Ratings of Sub-Criteria														
		C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}	C_{41}	C_{42}	C_{43}
K_1	K_1-D_1	G	F	G	F	VG	G	F	G	F	G	G	VG	G	F	G
	K_1-D_2	VG	G	G	G	G	VG	F	F	G	VG	G	VG	VG	G	G
	K_1-D_3	VG	G	G	G	G	VG	G	G	G	VG	G	G	G	G	VG
K_2	K_2-D_1	F	F	G	F	G	P	P	F	VG	G	G	G	G	G	F
	K_2-D_2	P	F	F	F	G	F	P	P	G	F	G	F	F	G	F
	K_2-D_3	F	G	P	F	P	P	P	P	G	F	G	G	G	F	G
K_3	K_3-D_1	VG	G	VG	G	G	VG	VG	VG	G	VG	G	VG	VG	VG	G
	K_3-D_2	VG	G	G	VG	F	VG	VG	G	VG	G	G	VG	VG	G	VG
	K_3-D_3	G	G	VG	VG	G	F	G	G	G	VG	VG	VG	VG	G	VG

	K_4-D_1	F	G	G	F	G	G	F	VG	F	VP	F	G	G	F	G
K_4	K_4-D_2	G	G	F	P	G	G	F	G	F	P	F	G	VG	F	F
	K_4-D_3	F	F	VG	G	F	F	G	G	F	P	P	VG	G	F	G
	K_5-D_1	VG	VG	VG	G	G	G	F	G	VG	G	G	VG	VG	VG	VG
K_5	K_5-D_2	G	VG	VG	VG	G	VG	G	G	VG	G	G	G	VG	G	VG
	K_5-D_3	VG	G	G	VG	VG	VG	G	G	G	VG	G	G	G	VG	VG
	K_6-D_1	G	G	G	F	G	G	VG	G	VG	F	G	F	F	G	G
K_6	K_6-D_2	G	VG	F	G	F	G	G	F	G	G	F	G	G	F	G
	K_6-D_3	G	G	VG	G	VG	G	G	G	G	G	F	F	G	F	G

4.1.3. Calculation of the PIKCV

In performance evaluation, we assume expert weights are equal and use Formula (10) to compute the aggregation of fuzzy linguistic evaluation values of sub-criteria. For example, the evaluation value of "Reliability" for K_1 is calculated as

$$\bar{S}_{11} = \Delta\left(\frac{1}{3}\sum \Delta^{-1}(s_3,0), \Delta^{-1}(s_4,0), \Delta^{-1}(s_4,0)\right) = \Delta(0.917) = (s_4, -0.083), \tag{29}$$

Similarly, the fuzzy aggregated ratings of each criterion of K_1 can be calculated, as shown in Table 5. For example, the aggregated rating value of "Knowledge validity" for K_1 is obtained by using Formula (11):

$$\begin{aligned} \bar{S}_1 &= \Delta\sum_{j=1}^{n_1}\left[\Delta^{-1}(r_{1j}, \alpha_{1j}) \cdot \bar{W}_{1j}^{C}\right] \\ &= \Delta\Big(\sum\left[\Delta^{-1}(s_4, -0.083)\times 0.393\right], \left[\Delta^{-1}(s_3, -0.083)\times 0.196\right], \\ &\quad \left[\Delta^{-1}(s_3, 0)\times 0.248\right], \left[\Delta^{-1}(s_3, -0.083)\times 0.163\right]\Big) \\ &= \Delta(0.786) = (s_3, 0.036) \end{aligned} \tag{30}$$

Based on the above steps, we can compute the PIKCV of six candidates' knowledge by using Formula (13), as shown in Table 6. For example, the PIKCV of K_1 is calculated as

$$\begin{aligned} PIKCV(K_1) &= \Delta\sum_{i=1}^{n}\left[\Delta^{-1}(r_i, \alpha_i) \cdot \bar{W}_i^{C}\right] \\ &= \Delta\Big(\sum\left[\Delta^{-1}(s_3, 0.036)\times 0.375\right], \left[\Delta^{-1}(s_3, 0.013)\times 0.213\right], \\ &\quad \left[\Delta^{-1}(s_3, 0.083)\times 0.271\right], \left[\Delta^{-1}(s_3, 0.032)\times 0.141\right]\Big) \\ &= \Delta(0.793) = (s_3, 0.043) \end{aligned} \tag{31}$$

Table 5. The aggregated results of fuzzy comprehensive evaluation for K_1.

Criteria and Sub-Criteria	Rating (K_1)			Fuzzy Evaluation (K_1)	Weighted Rating (K_1)	PIKCV (K_1)
	D_1	D_2	D_3			
Knowledge validity (B_1)						
Reliability (C_{11})	G	VG	VG	$(s_4, -0.083)$		
Accuracy (C_{12})	F	G	G	$(s_3, -0.083)$	$(s_3, 0.036)$	
Integrity (C_{13})	G	G	G	$(s_3, 0)$		
Normalization (C_{14})	F	G	G	$(s_3, -0.083)$		$(s_3, 0.043)$
Knowledge novelty (B_2)						
Technological innovation (C_{21})	VG	G	G	$(s_3, 0.083)$	$(s_3, 0.013)$	
Interdisciplinary application (C_{22})	G	VG	VG	$(s_4, -0.083)$		
Knowledge redundancy (C_{23})	F	F	G	$(s_2, 0.083)$		

Knowledge compatibility (C_{24})	G	F	G	$(s_3, -0.083)$	
Potential practicability (B_3)					
Technological advancement (C_{31})	F	G	G	$(s_3, -0.083)$	
Process feasibility (C_{32})	G	VG	VG	$(s_4, -0.083)$	$(s_3, 0.083)$
Process complexity (C_{33})	G	G	G	$(s_3, 0)$	
Environmental protection (C_{34})	VG	VG	G	$(s_4, -0.083)$	
Manufacturing profitability (B_4)					
Manufacturing quality (C_{41})	G	VG	G	$(s_3, 0.083)$	$(s_3, 0.032)$
Production costs (C_{42})	F	G	G	$(s_3, -0.083)$	
Production efficiency (C_{43})	G	G	VG	$(s_3, 0.083)$	

Table 6. The overall evaluation results and ranking of candidate knowledge.

	K_1	**K_2**	**K_3**	**K_4**	**K_5**	**K_6**
PIKCV	$(s_3, 0.043)$	$(s_2, 0.048)$	$(s_3, 0.120)$	$(s_2, 0.086)$	$(s_3, 0.122)$	$(s_3, -0.035)$
Ranking	3	6	2	5	1	4

4.2. Comparison and Analysis of Knowledge Evaluation Results

It may be seen in Table 6 that the PIKCV of alternative K_1, $(s_3, 0.043)$, represents slightly higher than "Good", and the alternative K_1 is worse than K_3, since K_3 is closer to the linguistic term s_4. The overall ranking of the six principle knowledge candidates is $K_5 \succ K_3 \succ K_1 \succ K_6 \succ K_4 \succ K_2$. K_5 is the best knowledge candidate with K_3 following thereafter. These aggregated results are consistent with experts' opinion. On the other hand, the overall evaluation result of K_1 is 0.39, which was calculated using the SWA method with the same data, as shown in Table 7. This translates into the degree of membership, which is 0.56 and 0.44. In other words, the overall evaluation result of K_1 is worse than "Fair" when applying the SWA method. It is obvious that the evaluation results obtained by the SWA method are not consistent with the opinions of the expert committee. Hence, to some extent, it demonstrates that the proposed method in this study can effectively aggregate fuzzy linguistic evaluation data among criteria and sub-criteria, and obtain reasonable overall evaluation results, while avoiding information loss.

Table 7. Evaluation results of K_1 using SWA method.

Criteria and Sub-Criteria	**Sub-Criteria Evaluation**	**Sub-Criteria Weight**	**Weighted Results in Criteria**	**Weights of Criteria**	**Overall Evaluation**
Knowledge validity (B_1)					
Reliability (C_{11})	0.81	0.81			
Accuracy (C_{12})	0.64	0.69	0.52	0.81	
Integrity (C_{13})	0.71	0.76			
Normalization (C_{14})	0.64	0.69			
Knowledge novelty (B_2)					
Technological innovation (C_{21})	0.76	0.81			
Interdisciplinary application (C_{22})	0.81	0.64	0.49	0.76	
Knowledge redundancy (C_{23})	0.57	0.64			0.39
Knowledge compatibility (C_{24})	0.64	0.69			
Potential practicability (B_3)					
Technological advancement (C_{31})	0.64	0.76			
Process feasibility (C_{32})	0.81	0.81	0.56	0.76	
Process complexity (C_{33})	0.71	0.76			
Environmental protection (C_{34})	0.81	0.69			
Manufacturing profitability (B_4)					
Manufacturing quality (C_{41})	0.76	0.81	0.53	0.64	
Production costs (C_{42})	0.64	0.76			

Production efficiency (C_{43})	0.76	0.64

From the perspective of 2-tuple linguistic expression, K_5 and K_3 have the same central value s_3 and their transitive values are close, so it may be determined that both offer superior knowledge innovation. Thus, they are expected to effectively support process innovation design in the context of particular application scenarios, yet other candidate knowledge should be improved based on the evaluation results of criteria and the corresponding sub-criteria. To achieve this potential application, the knowledge of these candidates could be further fused and refined on an open knowledge management platform.

4.3. Knowledge-Inspired Manufacturing Process Problem-Solving

Based on the above knowledge evaluation approach, a total of 265 knowledge items have been evaluated and improved for manufacturing process innovation of aerospace structures. In this section, the specific procedure for micro-turbine process problem-solving using process innovation knowledge will be briefly described.

The micro-turbine in this case is a core component of a micro turbojet engine and it has the following characteristics: (1) a complex curved structure and poor rigidity; (2) a thin blade prone to machining deformation; and (3) no through hole in the center of the turbine. Thus, it is difficult to manufacture using current manufacturing resources, as the core shaft positioning and clamping method, which is commonly used in general turbine machining, cannot be applied in this instance. Hence, it is necessary to solve the process problem of turbine manufacturing through innovation knowledge.

The process of innovative problem solving can be sub-divided into: process problem identification and formal description, process contradiction extraction and resolution, innovation scheme design, iterative solution and scheme optimization. The innovation process mainly involves several kinds of formal knowledge, as illustrated in Figure 4. Specifically, the main procedures for the micro-turbine process problem-solving are as follows:

(1) Process problem identification and formal description. With the help of PHS and PDT, the problem can be formally expressed as the specific information of "expectation and avoidance".
(2) Process contradiction extraction and resolution. According to the problem description, the innovation system can conveniently extract conflicting parameters, i.e., strengthening parameter and weakening parameter. Then, the innovative solving principles will be presented based on PCM, namely solving principles 1, 6, 7 and 9. These principles help to inspire the designer's creative thinking. Through a detailed analysis, two principle solutions (as shown in Figure 4) are considered effective in the problem-solving. By associating with MSE, an initial solution for thin-walled blade machining is obtained: Utilizing its cylindrical surface for clamping, but not handling the ball surface during this step.
(3) Innovation scheme design. With the support of ISI and MCD, we can design the detailed scheme in the existing manufacturing environment. After two iterations of conflict resolution, we get the scheme for spherical convex processing: By means of the threaded connection (its own structure/function) to realize positioning and clamping, and to ensure the dimensional precision of blades.

In this case, the innovative solutions of micro-turbine machining have been gradually revealed through multiple types of knowledge application and design thinking inspiration. We can see that quality evaluation and rational application of innovation knowledge are of great importance in innovation realization and the proposed method in this research is applicable for open manufacturing process innovation.

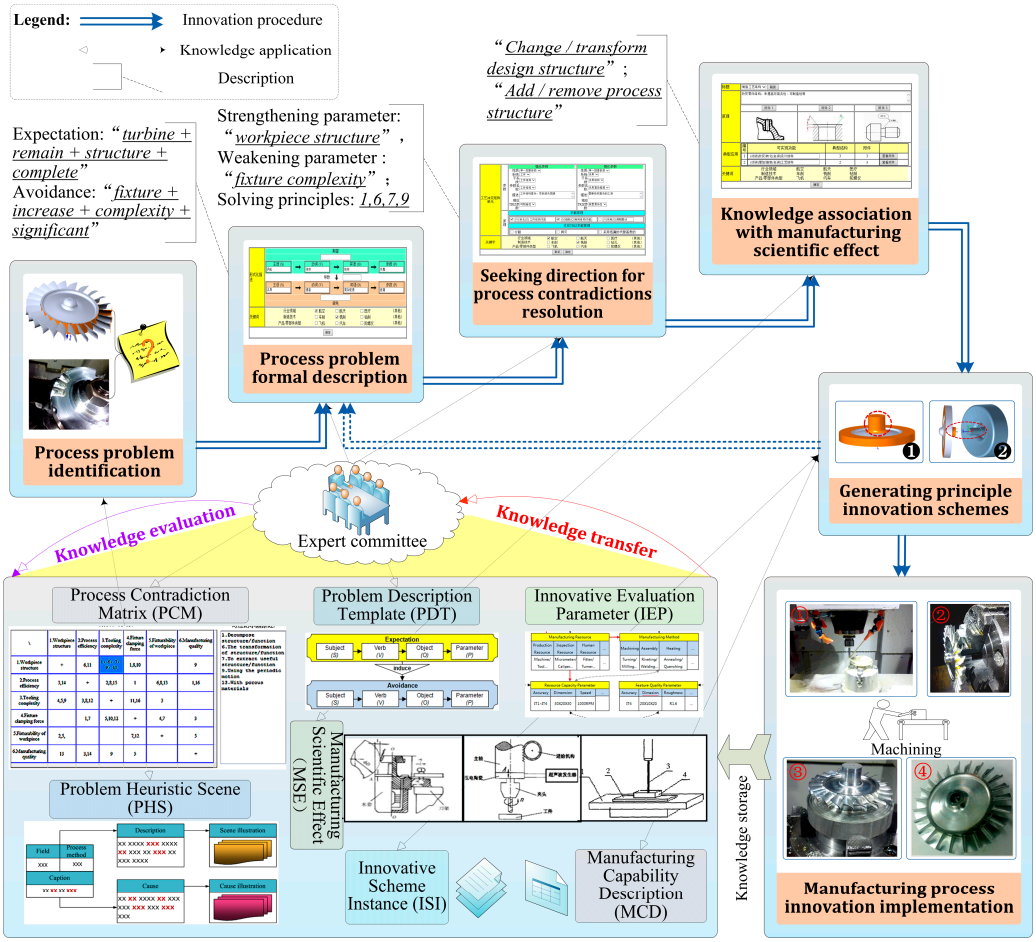

Figure 4. A micro-turbine process problem-solving by using process innovation knowledge.

5. Conclusions and Implications

5.1. Conclusions

As competition in global markets intensifies, process innovation has been recognized as a key factor for enhancing sustainable competitive advantage in manufacturing organizations. However, in the implementation of knowledge-driven CAPI, an important challenge that must be faced is how to evaluate and select appropriate process innovation knowledge from an open knowledge acquisition environment. In this paper, we have presented a manufacturing process innovation-oriented knowledge evaluation approach using MCDM and fuzzy linguistic computing. Some of the key contributions of this study are listed below:

- By considering process innovation knowledge characteristics and innovative applications, a comprehensive hierarchy evaluation index system is designed to measure the PIKCV, which can express the core value of knowledge in potential manufacturing innovation scenarios.
- A manufacturing process innovation-oriented knowledge evaluation model, based on AHP and fuzzy linguistic computing, is applied to effectively aggregate the evaluation value into the expert committee's comprehensive evaluation information in criteria weights and performance ratings. This model can meet the needs of rapid evaluation and selection of massive and multiple types of candidate knowledge in open innovation environments.
- A comparative analysis shows that the proposed method could obtain reliable evaluation results and avoid information loss during the processes of evaluation integration. Furthermore, an integrated procedure of knowledge capture, evaluation and process problem-solving for micro-turbine machining reflects the practicability of reliable and formalized knowledge in manufacturing process innovation design.

5.2. Limitations and Future Research

With regard to application instances, this paper has confirmed that the combination of MCDM and fuzzy linguistic computing can reasonably aggregate evaluation information from the expert committee for process innovation knowledge. From the perspective of continuous application of computer-aided innovation, a large amount of knowledge and data could be accumulated on the CAPI platform. It is necessary, therefore, for further studies to be conducted to consider objective evaluation and dynamic updating, based on knowledge application on the innovation system. In addition, reconciling mechanisms of experts' conflict evaluations should be further studied in practice.

The evaluation results in criteria and sub-criteria can provide a reference for knowledge improvement and this may contribute to effective knowledge evolution. The results highlighted in this paper can be broadly applied to open knowledge management practices of manufacturing enterprises. Future research will expand and deepen these results more comprehensively, including just-in-time knowledge recommendation for innovation design life cycle, integrated management of product design knowledge and process knowledge, optimal selection of innovation knowledge in cloud manufacturing environment, etc.

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Abbreviations

The following abbreviations are used in this manuscript:

CAPI	Computer-Aided Process Innovation
MCDM	Multi-Criteria Decision-Making
AHP	Analytic Hierarchy Process
CAPP	Computer-Aided Process Planning
CAM	Computer-Aided Manufacturing
PIKCV	Process Innovation Knowledge Comprehensive Value
SWA	Simple Weight Additive
PDT	Problem Description Template
PCM	Process Contradiction Matrix
MSE	Manufacturing Scientific Effect
ISI	Innovative Scheme Instance
MCD	Manufacturing Capability Description

Nomenclature

(s_i, α_i)	is a 2-tuple linguistic variable
$S=\{s_0, s_1, ..., s_g\}$	is a predefined linguistic term set
s_i	is the linguistic label from S
α_i	is the distance to the central value of the *i*th linguistic term
β	is a number value representing the aggregation result
Δ^{-1}	represents a reverse equation of the generalized translation function
$\overline{S}$	represents a arithmetic mean of 2-tuple fuzzy linguistic variable set
$E=\{E_1, E_2, ..., E_M\}$	is the established expert committee

$K=\{K_1,K_2,...,K_N\}$	is a set of candidate process innovation knowledge
$(s_{ijm}^w,\alpha_{ijm}^w)$	represents the 2-tuple fuzzy criteria weights of the *j*th sub-criteria regarding the *i*th criteria of the *m*th expert
A	is a judgment matrix
λ_{max}	is the largest eigenvalue of A
CR	is the consistency rate
W^C	is the fuzzy comprehensive weight set of knowledge evaluation
W^A	is the weighted weight set of the AHP expert group
W^L	is the aggregated weight set of fuzzy linguistic computing

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