Received February 4, 2019, accepted March 3, 2019, date of publication March 15, 2019, date of current version April 1, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2904759

Big Data-Oriented Product Infant Failure Intelligent Root Cause Identification Using Associated Tree and Fuzzy DEA

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This work was supported in part by the National Natural Science Foundation of China under Grant 61473017, and in part by the National Defense Pre-Research Foundation of China under Project 6140002050116HK01001 and Project 61400020108.

ABSTRACT Infant failure analyzing is an effective approach to improve production quality continuously. The root causes of infant failure have always been a puzzle to manufacturers. To satisfy the increasing demand for the fuzzy root cause analysis of product infant failure in the era of big data, a novel root cause identification approach based on the associated tree and fuzzy data envelopment analysis (DEA) is presented for product infant failure. First, to decrease fuzziness with regard to the mechanism of infant failure, the associated tree is adapted to guide the analysis process for possible root causes based on axiomatic domain mapping. Second, considering the fuzzy mechanism and massive data, the fuzzy DEA technique is adopted to cluster all the potential factors of functional parameters, physical parameters, and process parameters from big data regarding product life cycle. Third, the ranking method of decision-making unit efficiency in fuzzy DEA is used to model and rank the weight of each node in the established associated tree of infant failure. Finally, a case study of root cause identification for a typical infant failure of the vibration and noise of a washing machine is presented to demonstrate the feasibility and validity of the proposed method.

INDEX TERMS Infant failure, big data, root cause analysis, associated tree, fuzzy DEA.

I. INTRODUCTION

With the advent of Industry 4.0 and big data era, the Artificial Intelligence (AI) techniques should be widely adopted to the field of quality management and improvement [1]. The infant failure is deemed to be built in the manufacturing process, and infant failure root cause analysis is a routine task for quality managers of product manufacturers [2]–[4], which is also a challenge for most of manufacturers due to the non-intelligent analyzing means and vague understanding of its mechanism.

Infant failure frequently refers to failure that occurs in the ''infant'' region of the leftmost portion of bathtub curve of product life [5]. The majority of reliability failures are assumed to be infant mortality failures, and these failures are mostly attributed to hidden defects formed during the product design and manufacturing process. To ensure product reliability and quality from industrial batch production, the burn-in test is typically the only means to accelerate the screening of hidden defects [6]. Although this test is widely used to reduce infant failures in reliability engineering, studies on the root cause analysis of product infant failure are few. With the constant emergence of big data from the life cycle of complex engineering products, such as cars, root cause identification is becoming a key task in quality control, and the precision of results is crucial to prevent similar failures from occurring repeatedly [7], [8]. A number of studies have investigated infant failure with statistical methods, such as traditional infant failure rate modeling and bathtub-shaped failure rate modeling [9], [10]. Domma and Condino [11] proposed a new class model for survival data analysis. This model is characterized by the sign of the first derivative for the hazard rate by building two new distribution functions.

Failure mode and effect analysis (FMEA) and fault tree analysis (FTA) are generally utilized to identify failure causes and modes in engineering. Masayuki *et al.* [12] used the Axiomatic design to conduct failure data analysis and stressed

The associate editor coordinating the review of this manuscript and approving it for publication was Jiajie Fan.

that complex and coupled designs are the root causes of engineering failures. Pavasson *et al.* [13] proposed a variation mode and effect analysis (VMEA) method to identify the source of variation by identifying the key characteristics in the product development process that can be used as specific targets for quality improvement. Shukla *et al.* [14] proposed a methodology for optimal sensor allocation for root cause analysis that maximizes key characteristics, which include product characteristics and control characteristics in a multi-station assembly process. He *et al.* [2] presented a multilayered model structure for modeling infant failure rate by integrating and quantifying the influence of quality variations into the manufacturing process for electromechanical products. Tang *et al.* [15] proposed a weighted risk priority number (AMWRPN) based on the FMEA fuzzy metric, and by measuring the degree of ambiguity assessed by experts, the relative weights of different risk factors are determined.

Although several studies on root cause analysis have been conducted, most previous works have focused only on failure rate modeling and specific product failure analysis. In contrast with constant and wear-out failures, infant failures are the most complicated, and their root cause identification involves all the parameters originated in a product life cycle. That is, improper design, manufacturing defects, and operation errors can cause product infant failures. The formation mechanism of infant failure remains fuzzy due to its complexity, and a systematic identification approach for the fuzzy cognition of its root causes is rare. Therefore, a method for identifying the root causes from fuzzy big data for infant failure should be developed. In fact, the data of possible root causes for evaluation are frequently expressed fuzzily. That is, causal relationship of inputs and outputs are frequently represented in fuzzy numbers, which reflecting the preference experience of decision-making experts in the field of infant failure analysis. Fortunately, fuzzy data envelopment analysis (DEA) [16], [17] can be adopted to evaluate the relative efficiencies of decision-making units (DMUs) under an environment in which processing data cannot be precisely measured. Wen and Li [18] extended traditional DEA models to a fuzzy framework. A fuzzy DEA model based on credibility measure and a ranking method for all DMUs are also presented. To evaluate relative efficiency for multiple inputs and outputs, Puri and Yadav [19], [20] proposed a fuzzy DEA model to deal with the imprecise or fuzzy input/output data problem. Their proposed model can transform the fully fuzzy cost efficiency (CE) and revenue efficiency (RE) models into crisp linear programming problems. Garcia *et al.* [21] presented the possibility DEA model for FMEA and utilized the fuzzy DEA method to determine ranking indices among failure modes. Hossein and Arezoo [22] evaluated the priority and importance of each DMU by using TOPSIS and the FMEA model in an interval-valued intuitionistic fuzzy environment. Wen *et al.* [23] proposed a random spare part optimization model (SSOM) based on random DEA to improve the efficiency of solving the problem of spare parts optimization under fuzzy conditions. These strategies introduce a customized approach that targets inefficient DMUs to improve computation efficiencies. In addition, uncertainty and fuzziness in the health prediction and failure analysis process are increasingly emphasized in the failure analysis field. A fuzzy theory–gray model–support vector machine approach for an integrated health management system was proposed by Xu *et al.* [24]. Fuzzy intelligence methodologies should have been applied extensively to improve the accuracy of root cause analysis for infant failure.

The reliability theory based on fault physics tend to use fault mechanism model to describe regularity of fault occurrence, and the influence of uncertain factors on the regularity of fault occurrence is described by the dispersion of model parameters [25]. Hall and Strutt [26] proposed methodology based on physics-of-failure models to analyze the influence of model uncertainties and uncertain parameters on component reliability. The method based on physics of failure are always confined to reliability data, and lack of systematic research on early failure mechanism of products from the perspective of product reliability formation. Still, issues of root cause identification approach of product infant failure mechanism in the context of big data and from the perspective of product reliability formation for infant failure which should be developed and have not drawn the attention it deserves. Driven by these requirements, a new big data-oriented root cause identification approach based on the associated tree and fuzzy DEA is proposed in our study. The main contributions of this method are as follows:

1) The associated tree is adopted to collect all the possible root causes based on Axiomatic domain mapping from the big data of product life cycle, thereby decreasing the fuzziness of the mechanism of infant failure, and it provides a new means to guide the analysis process for infant failure mechanism, which can decrease the information illegibility.
2) In consideration of the fuzziness from imprecise or fuzzy input/output data problems of the collected big data, the fuzzy DEA technique is adopted to cluster all the potential factors of functional, physical, and process parameters from the big data collected from product life cycle. The fuzzy DEA algorithm is applied firstly to compute and analyze the weight of the possible root cause of infant failure,
3) Ranking method for DMU efficiency in fuzzy DEA is used to model and rank the relation weight of each node, which provides a feasible method to locate the weak risk parameters in infant failure mechanism analysis.

The rest of this paper is structured as follows. The mechanism of product infant failure and its fuzziness are explained in Section 2. Weight computation based on fuzzy DEA is analyzed in Section 3 with reference to the associated tree model. A numerical example of a typical infant failure of washing machine is presented in Section 4. Finally, conclusions regarding the study are drawn in Section 5.

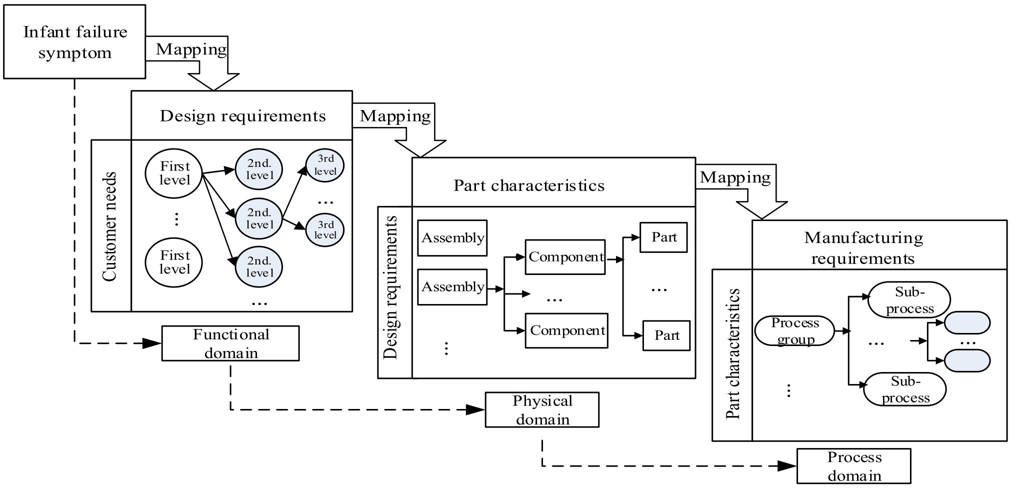

FIGURE 1. Associated tree framework of the root cause of product infant failure.

II. MECHANISM OF PRODUCT INFANT FAILURE AND ITS FUZZINESS

Undoubtedly, design or manufacturing defects cannot be completely prevented or eliminated by quality control in the product development process, thereby resulting in product failure during early use. That is, infant failure is typically caused by poor design, material defect, manufacturing defect, inadequate materials, poor inspection, quality variation, assembly error, poor workmanship and mishandling, and other human errors. Overall, infant failure is frequently caused by inherent defects formed throughout the life cycle of a product due to variation and uncertainty in design, manufacturing, assembly, and operation. Furthermore, inherent reliability established during manufacturing will directly determine the rate of product infant failure. Hence, the accumulation of quality deviations in manufacturing is generally accepted as the key cause of high infant failure rate [2].

A. CONSTRUCTING THE ASSOCIATED TREE OF PRODUCT INFANT FAILURE BASED ON AXIOMATIC DOMAIN MAPPING

As mentioned earlier, the formation mechanism of infant failure is currently fuzzy for most manufacturers. This study, which aims to decrease the fuzziness of the root causes of infant failure, builds an associated tree of product infant failure based on waterfall decomposition and mapping theory of functional, physical, and process domains in Axiomatic design [27], as shown in Fig. 1. The associated tree of product infant failure is a hierarchical tree of function requirements (FR), design parameters (DP), and process variables (PV) of a product.

In this figure, the established associated tree can help quality engineers set the hierarchical relationships of infant failure symptoms, function requirements (FR), design parameters (DP), and process variables (PV). In other words, the associated tree of product infant failure can be able to build the mapping relationship between associated tree and product assemble tree, which have contributed to analyze quality problem rooted deeply in product design schemes and variations of parameters in manufacturing process. In particular, failure symptoms are first decomposed into FRs in the functional domain. In this link, the first-level function nodes be decomposed sequentially and hierarchically by means of layer-by-layer analysis of design objects. Then, the identified FRs are decomposed into DPs in the physical domain according to the decomposition results of function domain. In this link, through the coding of each component, the corresponding subassemblies are obtained from the product data management (PDM) system. Finally, through the coding of each physical note, the corresponding sub-processes are obtained from the Enterprise Resource Planning (ERP) system. The skeptical DPs are decomposed into the corresponding manufacturing variables (PVs) in the process domain according to the results of physical decomposition and manufacturing scheme. FRs and DPs are determined in the design process, whereas PVs are built in the production process. Usage environmental stresses are the inducement factors of infant failures; therefore, the possible root causes of infant failure can be classified into design, production, and usage causes.

B. BIG DATA OF POSSIBLE ROOT CAUSES AND THEIR FUZZINESS

As shown in the established associated tree model of infant failure root cause, uncertain factors that cause imprecise or fuzzy identification results exist. To systematically identify the latent causes of infant failure, the big data of quality and reliability collected from the design, production, test, and usage of product life cycle comprise an indispensable database. The investigation on the product infant failure can effectively achieve root cause identification by data integrated from different stages benefit from big data. Different resources of data and different data with heterogeneous formats are collected. The data integrated from different steps of product life cycle in a unified manner to identify the latent causes of infant failure. As described earlier, fuzziness naturally exists in the root cause identification process, which is produced by big data from product life cycle. The big data of possible root causes and their fuzziness are shown in Fig. 2.

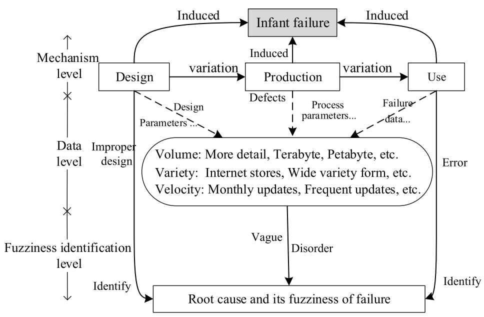

FIGURE 2. Big data of possible root causes and their fuzziness.

As shown in the figure, the big data-oriented infant failure root cause identification process is complex and involves multiple uncontrolled uncertainties. From the perspective of the established associated tree for product life cycle, the infant failure mechanism of a product is related to the variation accumulation of design, manufacturing, and usage factors. When the design stage is considered, functional specifications related to infant failure should be translated into detailed qualitative and quantitative physical and process parameters. The mapping vulnerabilities of infant failure symptoms between physical and process parameters are the source of design defects. Some of these design defects should be transformed into manufacturing defects by variation accumulation in a multilevel manufacturing process. Variations from human, machine, material, method, measurement, and environment (5M1E) result in quality-related failures, which will occur during usage stage due to overstress variation and finally result in product infant failure. However, fuzziness exists in this cognition of infant failure root cause and the root cause cannot be identified. Different designers, conditions of use, and part requirements indicate a different description of the method. In fact, determining whether an object belongs to a root cause is difficult due to the complexity of products, the ambiguity of the concept, and the vague extension. Therefore, fuzziness exists due to unclear definitions and vague criteria, which results in uncertainty.

From the preceding discussion, the mechanism of the generation and root cause identification of infant failure remains fuzzy. Moreover, big data from design, production, and use have different characteristics. Big data create unique features because of their volume, variety, and velocity, which are difficult to express accurately. As shown in Fig. 2, the volume of data from design, process, and usage parameters causes the storage of big data to reach terabyte or petabyte. Variety is typically reflected in various forms of existing documents, eye-tracking data, and sentiments about purchased products based on "Likes." In addition, velocity is usually reflected in frequent updates. In different stages of a product life cycle, performing real-time data processing is difficult due to the characteristics of big data. These multiple characteristics lead to a significant challenge in the analysis of big data from a product life cycle, which result in fuzzy qualitative and quantitative descriptions. The present study considers the vague data of root cause analysis from an associated tree model and uses triangular fuzzy numbers in the deburring process. A relationship matrix of the functional, physical, and structural domains can be used to express the correlation degree of each element. Failure probability, failure detectability, and fault severity can be used to measure the strength of the relationship matrix. Therefore, fuzziness fully exists in root cause analysis based on big data and should be defuzzified. This study uses fuzzy DEA to help analyze the root causes of product infant failure based on an associated tree.

III. WEIGHTS COMPUTATION BASED ON FUZZY DEA

Fuzzy DEA can provide a calculation method for weight evaluation based on the nodes of the output–input index, which helps obtain the node relation weight and quantitatively rank the whole associated tree.

A. FRAMEWORK OF WEIGHT COMPUTATION FOR THE ASSOCIATED TREE

The big data of possible root causes and their fuzziness in the associated tree are shown in Fig. 1. Effective data analytics methods that can handle fuzziness are required to address this issue. Accordingly, a fuzzy DEA-based data analytics approach is adopted to rank the weights of the associated tree of product infant failure based on the collected quality and reliability data for each node, which can fulfill the objective of this study and the systematic identification of root causes. Therefore, an analysis framework is proposed to compute the weight of the root cause analysis based on the fuzzy DEA method according to the identification framework of the associated tree of product infant failure shown in Fig. 1. The process of weight computation for each node in the proposed associated tree is illustrated in Fig. 3.

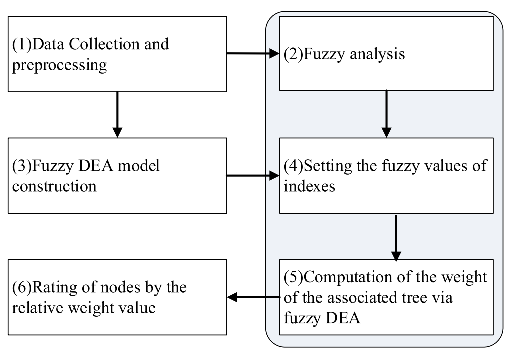

FIGURE 3. Weight computation of the associated tree based on the DEA analysis framework.

As shown in the above Fig.3, to identify root cause, the core task of the associated tree is node weight computation through fuzzy DEA, which is expounded as follows.

Step 1 (Data Collection and Preprocessing): On the basis of the framework of the associated tree of infant failure shown in Fig. 1, big data from the product data management system should be collected and preprocessed first. All possible causes originating from the design, production, and usage phases of product life cycle may be extracted from data information.

*Step 2 (Fuzzy Analysis):*The main task is to verify the advantage of utilizing triangular fuzzy number given the fact that not only the uncertainty in the involved data should be fully accounted for, but the expertise should also be fully represented. Therefore, considering the big data of possible root causes and their fuzziness shown in Fig. 2, the fuzzy DEA model that considers fuzzy number can be effective in dealing with uncertainty, which contains information that cannot be suitably accounted for and should be regarded as uncertain.

Step 3 (Fuzzy DEA Model Construction): The main task is to determine the suitable method for dealing with the weight computation of nodes in the associated tree. This study introduces fuzziness into the classical DEA–Banker, Charnes, and Cooper models, which can be regarded as an extension of the DEA methodology. In this study, we adopt the fuzzy DEA model to address fuzziness and use the ranking method based on the α-cut.

Step 4(Setting the Fuzzy Values of Indexes): Given the important task of fuzzy DEA in determining the input and output indicators, this step emphasizes the fuzzy value of indexes for root cause identification from big data. To ensure the accuracy of weight computation, designers should set fuzzy values with the aid of original quality data and their expertise and experience.

Step 5(Computation of the Weight of the Associated Tree via Fuzzy DEA):

The main task is to determine the relative efficiency of DMUs in the associated tree. In accordance with the fuzzy DEA model, efficiency scores that evaluate the weight of different DMUs in terms of the use of inputs and outputs originating from fuzzy indexes in the design and manufacture of product life cycle should be provided.

Step 6(Rating of Nodes by the Relative Weight Value): The main task for all the nodes of the functional, physical, and manufacturing trees of the presented associated tree is to rank the weight vectors of nodes based on their efficiency value. From Step 5, the efficiency value can be obtained by assessing the relative weight value and the rating process is based on the associated tree. The relative weight value of the process cell nodes can be calculated by means of the efficiency index of the nodes for the corresponding arithmetic operations of the triangular fuzzy number.

As shown in the preceding framework, the weight computation for the associated tree of product failure can be effectively performed via fuzzy DEA, and the details of fuzzy DEA theory are expounded in the subsequent section.

B. FUZZY DEA THEORY

Fuzzy DEA is a means to quantify vague data in which the inputs and outputs of DMUs are fuzzy variables. Suppose that each $\text{DMU}_j (j = 1, \cdots, n)$ has m different inputs $x_{ij}(i = 1, \cdots, m)$ and s different outputs $y_{rj}(r = 1, \cdots, s)$. With the aid of the fuzzy Charnes, Cooper, and Rhodes (CCR) model, the applicative fuzzy DEA [19], [20] model can be defined as follows.

The efficiency evaluation value is set as

$$h_j = \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{i=1}^{m} v_i x_{ij}$$

and the mathematic model of DMU_{j0} is

$$\begin{aligned} & h_{j0} = \sum_{r=1}^{s} u_r y_{rj0} \Big/ \sum_{i=1}^{m} v_i x_{ij0} \\ & s.t. \sum_{r=1}^{s} u_r y_{rj} \Big/ v_i x_{ij} \leq 1; \\ & \quad v \geq 0, \quad u \geq 0, \ j = 1, 2, \cdots, n; \end{aligned} \tag{1}$$

where $u_r(r = 1, \cdots, s)$ and $v_i(i = 1, \cdots, m)$ are the weights on the *rth* output and *ith* input. Through transformation with the CCR model, the model is presented as

$$\begin{aligned} & \text{Max } \text{h}_0 = \mu^T \text{Y}_0 \\ & s.t. \ \omega^T X_j - \mu^T Y_j \geq 0; \\ & \quad \omega^T X_0 = 1; \quad \omega \geq 0, \ \mu \geq 0, \ j = 1, 2, \cdots, n. \end{aligned} \tag{2}$$

The fuzzy DEA of the CCR model can be expressed as

$$\begin{aligned} & \text{Max } \tilde{\text{h}}_0 = \sum_{r=1}^{s} \mu_r \tilde{y}_{r0} \\ & s.t. \ \sum_{i=1}^{m} \omega_i \tilde{x}_{i0} = \tilde{1}; \\ & \quad \sum_{r=1}^{s} \mu_r \tilde{y}_{ij} - \sum_{i=1}^{m} \omega_i \tilde{x}_{ij} \leq 0; \\ & \quad \omega \geq 0, \quad \mu \geq 0, \ j = 1, 2, \cdots, n; \end{aligned} \tag{3}$$

where $\sim$ denotes fuzziness.

The fuzzy input is in the form of $\tilde{x} = (x^L, x^M, x^R)$ and the fuzzy output is in the form of $\tilde{y} = (y^L, y^M, y^R)$, where $x^L \leq x^M \leq x^R$ and $y^L \leq y^M \leq y^R$. Therefore, the fuzzy DEA–CCR model is presented as follows:

$$\begin{aligned} & \text{Max } \tilde{\text{h}}_0 = \sum_{r=1}^{s} \mu_r (y_{r0}^L, y_{r0}^M, y_{r0}^R) \\ & s.t. \ \sum_{i=1}^{m} \omega_i (x_{i0}^L, x_{i0}^M, x_{i0}^R) = (1^L, 1, 1^R); \\ & \quad \sum_{r=1}^{s} \mu_r (y_{rj}^L, y_{rj}^M, y_{rj}^R) - \sum_{i=1}^{m} \omega_i (x_{ij}^L, x_{ij}^M, x_{ij}^R) \leq 0. \end{aligned} \tag{4}$$

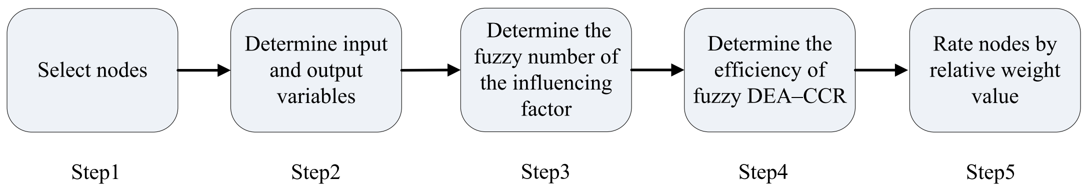

FIGURE 4. Proposed procedure for weight computation utilizing fuzzy DE–CCR.

C. WEIGHT COMPUTATION ALGORITHMS

From the preceding discussions, fuzzy DEA can be used to quantitatively rank the whole associated tree by its efficiency value. Accordingly, the next task is to fully use the efficiency of fuzzy DEA as the basis for computing weight. As shown in Fig. 2, fuzzy data can be collected in a bottom-up manner by considering the proposed associated tree in product life cycle. Therefore, with regard to the complexity and potential terminal nodes of each stage in the associated tree, we applied the bottom-up manner and started the weight computation from parts, components, and assemblies using the proposed method. The proposed procedure for weight computation that utilizes fuzzy DEA–CCR is shown in Fig. 4.

Step 1(Select Nodes): The task is to identify a limited number of nodes as operation objects. When numerous nodes exist, batch calculation is required to deal with the number of nodes in the associated tree. Thus, we use $\mathrm{EC_j}$ $j = 1, 2, \cdots, n$ to express each process node.

Step 2(Determine Input and Output Variables): Fuzzy DEA is used to calculate the characteristics of process variables. Each process variable is considered as a decision-making cell, and the evaluation value decision cell may reflect the relative importance of process variables. DEA should determine the input and output indexes. If the input is higher and the output is smaller, then the decision cell is poor. Therefore, if a factor value in the decision cell is large and the importance of the decision cell is higher, then this factor should be included as an output index; however, if a decision cell is greater than the value of certain factors and the degree of importance of the decision cell is lower, then this factor should be used as an input indicator [28]. In accordance with this principle, if the degree of association between a child node and a parent node is high for a process variable, then the child node is important. Thus, the association degree of the parent node with the relationship can be regarded as an output indicator, which can be presented as a correlation matrix. When the correlation degree of the modified autocorrelation matrix is given, if the impact is serious for cost and technical environmental factors, then the importance degree of the node is low. Thus, the influence degree of the sub-indexes on the failure correlation weight of the process node is used as an input indicator.

Step 3(Determine the Fuzzy Number of the Influencing Factor): This task determines the influencing factor and its evaluation fuzzy number of nodes. In this study, the triangular fuzzy number is used to quantify the subjective evaluation of fuzziness of a designer. In accordance with the two characteristics of the process, i.e., quality and reliability, and the property of the process node, five input indexes are used, as shown as Table 2. The index impact factor is denoted by $IF = (IF_1, IF_2, \cdots, IF_s)$.

This study adopts the triangular fuzzy number [29] to quantify the subjective assessment of the relative importance of the individual index via linguistic terms. M = (L, M, R) is set, and its membership function $\mu_M(x) : R \to [0, 1]$ can be described as follows:

$$\mu_M(x) = \begin{cases} 0, & otherwise \\ (x - \mathrm{L})/(M - L), & L \le x \le M \\ (R - x)/(R - M), & M \le x \le R, \end{cases}$$

where L, M, and R represent the lower, mean, and upper bounds, respectively. Assume that the decision-makers adopt the linguistic variable to reflect the weighting set W, as described in Table 1.

TABLE 1. Triangular fuzzy conversion.

Fuzzy important weight	Linguistic variable	Triangular fuzzy number
fw_1 (VLI)	Very less important	(0.05, 0.15, 0.25)
fw_2 (LI)	Less important	(0.2, 0.3, 0.4)
fw_3 (WI)	Weakly important	(0.35, 0.45, 0.55)
fw_4 (EI)	Equally important	(0.5, 0.6, 0.7)
fw_5 (MI)	More important	(0.65, 0.75, 0.85)
fw_6 (VI)	Very important	(0.8, 0.9, 1)

The triangular fuzzy conversion scale is presented in Fig. 5.

Step 4(Determine the Efficiency of Fuzzy DEA–CCR): For $IF = (IF_1, IF_2, \cdots, IF_s)$, given that this influencing factor reflects the importance of its indictors, we use constraint μ_{r0} to reflect the importance of the indicators of different nodes. $\mu_r = \sigma_r \mu_1, \quad r = 1, 2, \cdots, s$, and $\sigma_1 = 1$, $\sigma_r = IF_r/IF_1$ are set.

TABLE 2. Transaction data table.

TID	FR1	...	FR1313	DP1	…	DP13223	PV1	…	PV1344	Index1	…
1	1	0	1	1	1	1	1	1	0	1	0
2	0	0	1	0	1	0	0	0	1	1	1
3	1	0	1	1	0	1	1	1	0	1	0
4	1	0	1	0	1	0	1	0	1	0	1
…	…	…	…	…	…	…	…	…	…	…	…
10000	0	1	0	1	0	1	1	1	0	1	1

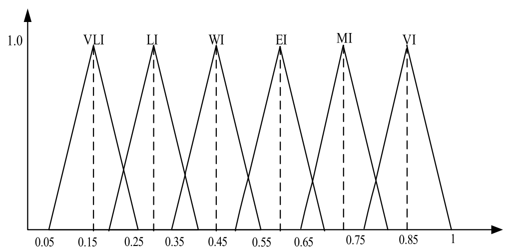

FIGURE 5. Linguistic scale for conversion proportion.

Therefore, in accordance with the input and output of the triangular fuzzy number, the CCR model can be expressed as follows:

$$\begin{aligned}
&\text{Max } \tilde{h}_0 = \sum_{r=1}^{s} \sigma_r \mu_1 (y_{r0}^L, y_{r0}^M, y_{r0}^R) \\
&s.t. \sum_{i=1}^{m} \omega_i (x_{i0}^L, x_{i0}^M, x_{i0}^R) = (1^L, 1, 1^R); \\
&\quad \sum_{r=1}^{s} \sigma_r \mu_1 (y_{rj}^L, y_{rj}^M, y_{rj}^R) - \sum_{i=1}^{m} \omega_i (x_{ij}^L, x_{ij}^M, x_{ij}^R) \leq 0; \\
&\quad \omega_i \geq 0, \quad \mu_r \geq 0, \; j = 1, 2, \cdots, n.
\end{aligned} \tag{5}$$

The objective function is $Max\ \mu_1$ after conversion.

For model (5), one widely used method for solving this programming problem is α-cut. The minimum level of possibility α and a nonlinear programming (NLP) model are given as follows:

$$\begin{aligned}
&\text{Max } \tilde{h}_0 = \sum_{r=1}^{s} \sigma_r \mu_1 [y_{r0}^L, y_{r0}^M, y_{r0}^R] \\
&\text{Subject to} \sum_{r=1}^{s} \mu_r [\alpha y_{rj}^M + (1-\alpha) y_{rj}^L] - \sum_{i=1}^{m} \\
&\qquad\qquad \omega_i [\alpha x_{ij}^M + (1-\alpha) x_{ij}^L] \leq 0; \\
&\quad \sum_{r=1}^{s} \mu_r [\alpha y_{rj}^M + (1-\alpha) y_{rj}^R] - \sum_{i=1}^{m} \\
&\qquad\qquad \omega_i [\alpha x_{ij}^M + (1-\alpha) x_{ij}^R] \leq 0; \\
&\quad \sum_{i=1}^{m} \omega_i (x_{i0}^L, x_{i0}^M, x_{i0}^R) = (1^L, 1, 1^R); \\
&\quad \omega_i \geq 0, \quad \mu_r \geq 0, \; j = 1, 2, \cdots, n.
\end{aligned} \tag{6}$$

Through this NLP, we can calculate the value of the efficiency index of a node $\tilde{h}_0$ by using the object value. This index value reflects the significance of the node. For n nodes, the final calculation is $\tilde{h}_j j = 1, 2, \cdots, n$. $\tilde{h}_j = (h_j^L, h_j^M, h_j^R)$ is set. We use the centroid method to defuzzify as follows:

$$f(\tilde{h}_j) = (h_j^L + h_j^M + h_j^R)/3. \tag{7}$$

Step 5(Rate Nodes by Relative Weight Value): The task in this step is to calculate the weight vectors of nodes using their relative closeness. From Step 4, the efficiency index of a node $\tilde{h}_0$ and the defuzzification value $f(\tilde{h}_j)$ can be computed. After normalization, the final weight of the node EC_j can be calculated using the following formula:

$$W_j = f(\tilde{h}_j) \Big/ \sum_{j=1}^{n} f(\tilde{h}_j). \tag{8}$$

Therefore, the maximum weight W_j can be used to reasonably and methodically rate nodes from the process, physical, and function domains in the associated tree.

IV. CASE STUDY

A. BACKGROUND

During the early usage of washing machines, the problem of the common vibration and noise failure of washing machine body is always the No.1 customer complaint. It is a typical infant failure of washing machine, and how to identify the formation mechanism and identify the root causes of this failure in the context of big data is always a dilemma for washing machine manufacturers. In this study, a washing machines in batch manufacturing is selected to identify root cause and potential vulnerabilities of the vibration and noise failure of washing machine body through mining these heterogeneous big data with fuzziness from different in the life cycle of the product (Fig.1). These data include product design, process design, and manufacturing information.

B. CONSTRUCTING THE ASSOCIATED TREE OF THE FAILURE ROOT CAUSE MODEL

The associated tree of failure root cause is established according to the failure symptom of the vibration and noise of a washing machine body and by using Axiomatic domain mapping theory and waterfall type decomposition theory, the final result is shown in Fig. 6.

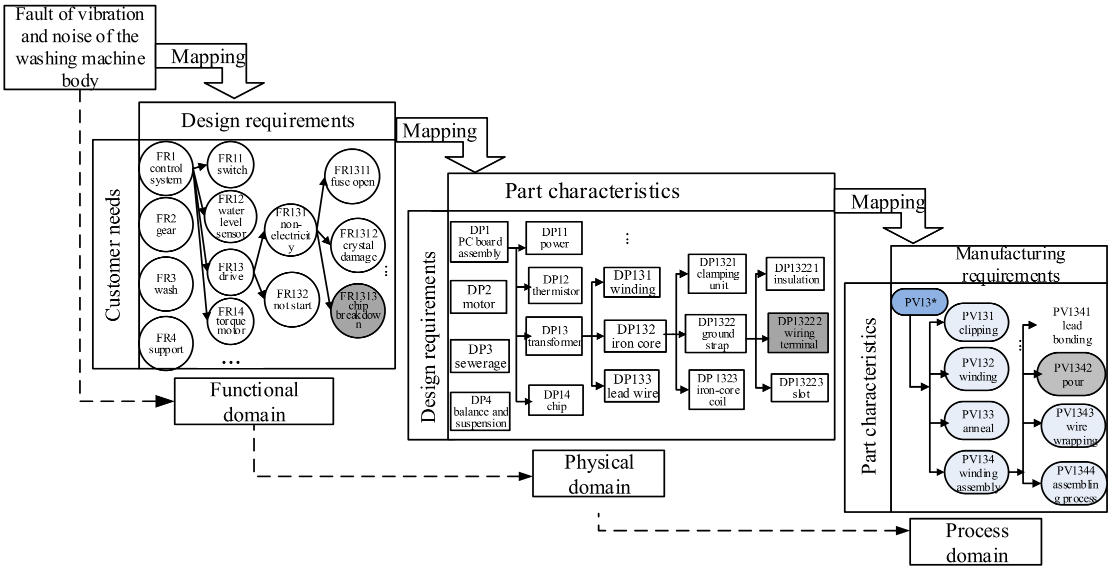

FIGURE 6. Associated tree model of infant fault vibration and noise of a washing machine body.

As shown in the Fig.6, the design requirements, corresponding part characteristics, corresponding manufacturing requirements are all obtained from these collected big data in product lifecycle, which provide the basic components to construct the associated tree of the selected infant failure.

In practical engineering applications, the infant failure result of a product varies due to different causes, such as errors from the design, physical, and manufacturing stages. With the input and use of a product, a large amount of related transaction record data is generated in the manufacture, production, usage, and maintenance of a product. In the era of big data, knowing how to mine specific rules and deriving a meaningful relationship model from these seemingly insignificant and disorderly big data is important. Analyzing the root causes of product infant failure from the design and manufacturing processes is useful, necessary, and can improve the utilization rate and reliability of a product.

Based on the big data collected, the actual faulted module for this type of washing machine is obtained via the product lifecycle management (PLM) system. This study uses 10000 simulation failure data as the transaction record data for the product failure maintenance test phase. This simulation data of the case study come from the actual industrial practice. For these data, if the property of a certain stage encounters a problem in the product failure test, then it is marked as 1. If the property is normal, then it is marked as 0. The transaction data are provided in Table 2.

A large number of transaction data are generated in Table 2, and the associated tree shown in Fig. 6 is combined with knowledge of mathematical statistics and probability. We use PV13 as the parent node, and PV131, PV132, and PV133 as sub-nodes to analyze transaction data, and thus, we can obtain the direct correlation degree between these nodes and the inspection index in the product maintenance process. For example, the total failure transaction data are denoted by N, PV131 and index(i) occur Q times, and the correlation degree (denoted as $p(i)$) between PV131 and $index(i)$ is $p(i) = Q/N$.

Through the preceding discussion, we take the corresponding DMU and transformed the input and output indicators $index(i)$ into triangular fuzzy numbers, as shown in Table 5. In the case study, PV13 is regarded as the object node, and the correlation degree and the triangular fuzzy numbers are presented in Table 3.

TABLE 3. Degree of correlation and triangular fuzzy number.

Fuzzy important weight	Linguistic variable	Triangular fuzzy number	Value
fw_1 (VLI)	Very less important	(0.05, 0.15, 0.25)	0.15
fw_2 (LI)	Less important	(0.2, 0.3, 0.4)	0.3
fw_3 (WI)	Weakly important	(0.35, 0.45, 0.55)	0.45
fw_4 (EI)	Equally important	(0.5, 0.6, 0.7)	0.6
fw_5 (MI)	More important	(0.65, 0.75, 0.85)	0.75
fw_6 (VI)	Very important	(0.8, 0.9, 1)	0.9

C. WEIGHT COMPUTATION

Step 1(Choose Nodes): The manufacturing process is the main cause of early failure, and thus, this study selects this

TABLE 4. Failure association weight evaluation index of nodes.

Number	Index1	Index2	Index3	Index4	Index5
Name	Variation possibility	Variation effect	Failure probability	Chance of undetected failure	Severity of failure effect
Influencing factor	0.15	0.25	0.15	0.15	0.3

process as the main case analysis. We focus on process node PV13 (transformer assembly process), and select tertiary nodes PV131 (cutting), PV132 (winding), PV133 (annealing), and PV134 (winding assembly) as object nodes to calculate their weights.

Step 2(Determine Output Indicator Variables): Operational and technological costs are considered in fuzzy DEA. This performance attribute is mostly concerned with the cost of acquiring the necessary operation and technology and the amount of money invested in design and manufacturing. From the perspective of manufacturers, this attribute shows how much capital has been used for product. Hence, operational and technological costs, together with technical environment factors, are used as input indicators. When these indicators are serious, the importance degree of a node is low. Furthermore, we select the relationship of nodes as the output index and use five output indexes, namely, variation possibility, variation effect, failure probability, chance of undetected failure, and severity of failure effect, as output indicators to evaluate the relationship.

Step 3(Determine the Fuzzy Number of the Influencing Factor):

Triangular fuzzy numbers are used to construct the impact failure association weight node evaluation index. Association weight evaluation indexes and their influencing factors are constructed based on historical data and expert experience, as shown in Table 4.

PV13 is taken as an object. We focus on PV131, PV132, PV133, and PV134. The corresponding index evaluation of nodes is transformed into a fuzzy number according to the five indexes, as shown in Table 5.

TABLE 5. Fuzzy evaluation values of nodes.

Node	Index1	Index2	Index3	Index4	Index5
PV131	MI	EI	VLI	VI	VLI
PV132	EI	VI	EI	EI	LI
PV133	WI	MI	LI	MI	VI
PV134	VLI	LI	WI	VI	EI

The triangular fuzzy matrix is transformed into a fuzzy normalized triangular fuzzy number using the conversion scale, and the results are presented in Table 6.

When fuzzy DEA is considered, and cost and technical environment factors are regarded as input indicators, the importance degree of the node is low when the impact is serious. This study presents the fuzzy number of input indicators provided by experts in Table 7.

Step 4(Determine the Efficiency of Fuzzy DEA–CCR):

EC1 (PV131) is presented as an example. The efficiency evaluation value is, Max $\tilde{h}_j$ shown at the bottom of this page.

$$
\begin{aligned}
&\text{Max } \tilde{h}_j = (0.65,0.75,0.85)\mu_1 + (0.5,0.6,0.7)\mu_2 + (0.05,0.65,0.25)\mu_3 + (0.8,0.9,1)\mu_4 + (0.05,0.65,0.25)\mu_5 \\
&\text{Subject to } (0.5,0.75,0.92)\omega_1 + (0.83,1,1)\omega_2 = \tilde{1} \\
&\qquad (0.65,0.75,0.85)\mu_1 + (0.5,0.6,0.7)\mu_2 + (0.05,0.65,0.25)\mu_3 + (0.8,0.9,1)\mu_4 + (0.05,0.65,0.25)\mu_5 \\
&\qquad - (0.5,0.75,0.92)\omega_1 - (0.83,1,1)\omega_2 \le \tilde{0} \\
&\qquad (0.5,0.6,0.7)\mu_1 + (0.8,0.9,1)\mu_2 + (0.5,0.6,0.7)\mu_3 + (0.5,0.6,0.7)\mu_4 + (0.2,0.3,0.4)\mu_5 \\
&\qquad - (0.33,0.42,0.67)\omega_1 - (0.083,0.25,0.42)\omega_2 \le \tilde{0} \\
&\qquad (0.35,0.45,0.55)\mu_1 + (0.65,0.75,0.85)\mu_2 + (0.2,0.3,0.4)\mu_3 + (0.65,0.75,0.85)\mu_4 + (0.8,0.9,1)\mu_5 \\
&\qquad - (0.5,0.75,0.92)\omega_1 - (0.33,0.42,0.67)\omega_2 \le \tilde{0} \\
&\qquad (0.05,0.65,0.25)\mu_1 + (0.2,0.3,0.4)\mu_2 + (0.35,0.45,0.55)\mu_3 + (0.8,0.9,1)\mu_4 + (0.5,0.6,0.7)\mu_5 \\
&\qquad - (0.83,1,1)\omega_1 - (0.5,0.75,0.92)\omega_2 \le \tilde{0} \\
&\qquad \mu_2 = 1.67\mu_1; \quad \mu_3 = \mu_1; \; \mu_4 = \mu_1; \; \mu_5 = 2\mu_1; \\
&\qquad \mu_i \ge 0 (i = 1, \cdots, 5); \quad \omega_i \ge 0 (i = 1, 2);
\end{aligned}
$$

TABLE 6. Normalized fuzzy matrix.

Node	Index1	Index2	Index3	Index4	Index5
EC_1(PV131)	(0.65, 0.75, 0.85)	(0.5, 0.6, 0.7)	(0.05, 0.65, 0.25)	(0.8, 0.9, 1)	(0.05, 0.65, 0.25)
EC_2(PV132)	(0.5, 0.6, 0.7)	(0.8, 0.9, 1)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)	(0.2, 0.3, 0.4)
EC_3(PV133)	(0.35, 0.45, 0.55)	(0.65, 0.75, 0.85)	(0.2, 0.3, 0.4)	(0.65, 0.75, 0.85)	(0.8, 0.9, 1)
EC_4(PV134)	(0.05, 0.65, 0.25)	(0.2, 0.3, 0.4)	(0.35, 0.45, 0.55)	(0.8, 0.9, 1)	(0.5, 0.6, 0.7)

TABLE 7. Fuzzy number of input indicators.

Input indicators	EC_1(PV131)	EC_1(PV132)	EC_1(PV133)	EC_1(PV134)
Cost	(1/2, 3/4, 11/12)	(1/3, 5/12, 2/3)	(1/2, 3/4, 11/12)	(5/6, 1, 1)
Technical environment	(5/6, 1, 1)	(1/12, 1/4, 5/12)	(1/3, 5/12, 2/3)	(1/2, 3/4, 11/12)

The linear programming with fuzzy coefficients is obtained as follows:

$$
\begin{aligned}
&\text{Max } \tilde{h}_j = (2.435{,}4.602{,}3.769)\mu_1 \\
&\text{Subject to } (0.5, 0.75, 0.92)\omega_1 + (0.83, 1, 1)\omega_2 = \tilde{1} \\
&\quad (2.435, 4.602, 3.769)\mu_1 - (0.5, 0.75, 0.92)\omega_1 \\
&\qquad -(0.83, 1, 1)\omega_2 \leq \tilde{0} \\
&\quad (3.236, 3.903, 4.57)\mu_1 - (0.33, 0.42, 0.67)\omega_1 \\
&\qquad -(0.083, 0.25, 0.42)\omega_2 \leq \tilde{0} \\
&\quad (3.8855, 4.5525, 5.2195)\mu_1 - (0.5, 0.75, 0.92)\omega_1 \\
&\qquad -(0.33, 0.42, 0.67)\omega_2 \leq \tilde{0} \\
&\quad (2.534, 3.701, 3.868)\mu_1 - (0.83, 1, 1)\omega_1 \\
&\qquad -(0.5, 0.75, 0.92)\omega_2 \leq \tilde{0} \\
&\quad \mu_1 \geq 0; \quad \omega_i \geq 0 (i = 1, 2);
\end{aligned}
$$

Set $\alpha = 0.8$. The multi-objective programming is

$$
\begin{aligned}
&\text{Max } \tilde{h}_j = \mu_1 \\
&\text{Subject to } 0.5\omega_1 + 0.83\omega_2 \leq 1; \\
&\quad 0.75\omega_1 + \omega_2 = 1; \\
&\quad 0.92\omega_1 + \omega_2 \geq 1; \\
&\quad 4.1686\mu_1 - 0.7000\omega_1 - 0.9660\omega_2 \leq 0; \\
&\quad 3.7696\mu_1 - 0.4020\omega_1 - 0.2166\omega_2 \leq 0; \\
&\quad 4.4191\mu_1 - 0.7000\omega_1 - 0.4020\omega_2 \leq 0; \\
&\quad 3.4676\mu_1 - 0.9660\omega_1 - 0.7000\omega_2 \leq 0; \\
&\quad 4.4354\mu_1 - 0.7840\omega_1 - 1.0000\omega_2 \leq 0; \\
&\quad 4.0364\mu_1 - 0.4700\omega_1 - 0.2840\omega_2 \leq 0; \\
&\quad 4.6859\mu_1 - 0.7840\omega_1 - 0.4700\omega_2 \leq 0; \\
&\quad 3.7344\mu_1 - 1.0000\omega_1 - 0.7840\omega_2 \leq 0; \\
&\quad \mu_1 \geq 0; \quad \omega_i \geq 0 (i = 1, 2);
\end{aligned}
$$

This linear programming problem is solved by Lindo, $\mu_1 = 0.1421902$. The efficiency evaluations of EC_1(PV131), EC_2(PV132), EC_3(PV133), and EC_4(PV134) are $0.1421902 \cdot (2.435{,}4.602{,}3.769)$, $0.2539110 \cdot (3.236{,}3.903{,}4.57)$, $0.1421902 \cdot (3.8855{,}4.5525{,}5.2195)$, and $0.1066426 \cdot (2.534{,}3.701{,}3.868)$, respectively. The result can be calculated using equation (6):

$$
\begin{aligned}
&f(\tilde{h}_1) = \frac{(0.3462+0.6544+0.5359)}{3} = 0.50705, \\
&f(\tilde{h}_2) = 0.9811, f(\tilde{h}_3) = 0.64085, \\
&f(\tilde{h}_4) = 0.35555.
\end{aligned}
$$

Step 5(Rate the Nodes by Relative Weight Value): After nominalization, Equation (7) is used. The relative weights of EC_1(PV131), EC_2(PV132), EC_3(PV133), and EC_4(PV134) are $w_1 = \frac{0.50705}{0.50705+0.9811+0.64085+0.35555} = 0.2041$, $w_2 = 0.3949$, $w_3 = 0.2579$, and $w_4 = 0.1431$, respectively.

Thus, the priority of node ranking is

$$EC_2(PV132) > EC_3(PV133) > EC_1(PV131) > EC_4(PV134).$$

D. RESULTS AND DISCUSSIONS

Similarly, we focus on DP134. The relative weights of $EC_1(PV1341)$, $EC_2(PV1342)$, $EC_3(PV1343)$, and $EC_4(PV1344)$, are 0.1864, 0.3717, 0.3093, and 0.1327, respectively. The priority ranking of nodes is

$$EC_2(PV1342) > EC_3(PV1343) > EC_1(PV1341) > EC_4(PV1344).$$

After the relative weights of all the nodes from the manufacturing domain were calculated, the weights of the nodes from the physical and functional domains could be computed using the proposed method. The final results show that the nodes of FR1313, DP13222, and PV1342 are the top three causes of infant fault vibration and noise of the washing machine body, as shown in Fig. 5.

Table 8 presents the efficiencies of different nodes (DMUs) for different α values. Different sets of values will acquire different efficiency values. A high efficiency shows that the corresponding DMU is important. With an increased level

TABLE 8. Efficiency of different nodes (DMUs) for different α values.

Nodes (DMUs)	α					
	0	0.2	0.4	0.6	0.8	1
DMU1 (EC_1)	0.4849	0.4911	0.4968	0.5021	0.5070	0.5116
DMU2 (EC_2)	0.9382	0.9502	0.9613	0.9716	0.9811	0.9900
DMU3 (EC_3)	0.6128	0.6207	0.6279	0.6346	0.6408	0.6467
DMU4 (EC_4)	0.3400	0.3443	0.3484	0.3521	0.3555	0.3588

of α value, the corresponding efficiency of the evaluation value also increases. When α=1, the value of the efficiency of nodes(DMUs) is the maximum. From this table, the value of the efficiency of DMU (EC_2) is the maximum. For different α values, the corresponding efficiency values are higher than 0.93, which shows that this process is the most important in manufacturing. Therefore, it should be strictly controlled in the design and manufacturing processes. The failure of EC_2 (PV132) may lead to the failure of PV13; that is, the process of PV132 is the root cause. Similarly, the efficiency values of EC_4 are less than 0.5, which indicates that the corresponding process phase is less important compared with EC_2. Furthermore, the assessment results for the efficiency of the DMUs according to different α levels are shown in Fig. 7.

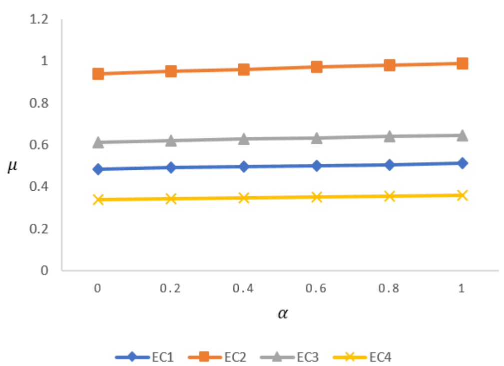

FIGURE 7. Assessment results of the efficiency of DMUs.

As shown in Fig. 7, the evaluation values for the efficiency of the four DMUs increase with an increase in the α level, and the rank of importance degree of each DMU is EC2 > EC3 > EC1 > EC4. That is, PV132 > PV133 > PV131 > PV134. The result in this paper are coincident with the result of engineering practice.

V. CONCLUSION

In this study, a novel big data-oriented root cause identification approach based on fuzzy DEA is proposed with the help of an established failure associated tree. First, the associated tree is adopted to guide the analysis process for possible root causes based on Axiomatic domain mapping to decrease the fuzziness of infant failure mechanism. Second, in consideration of the fuzzy mechanism and big data, the fuzzy DEA technique is adopted to cluster all the potential factors of functional, physical, and process parameters from the big data collected from product life cycle. Third, the ranking method for DMU efficiency in fuzzy DEA is used to model and rank the weight of each node in the established associated tree of infant failure. Finally, a case study of root cause identification for a typical infant failure of the vibration and noise of a washing machine is presented to demonstrate the feasibility and validity of the proposed method.

In conclusion, the proposed technique can cope with the root cause identification in an imbalanced or fuzzy dataset environment, and extract associations or causal relationships can be identified from the fuzzy big data collected from product life cycle. However, effectively mining vague big data of failure symptoms and quality inspection to compute the weights of nodes of high-dimensional structure based on dimensionality reduction requires further study.

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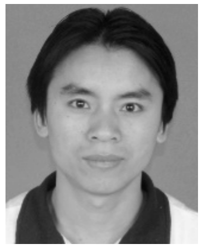

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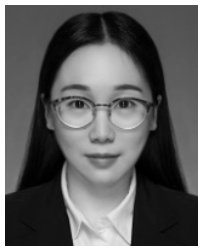

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