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Research Article

Component Importance Measure Computation Method Based Fuzzy Integral with Its Application

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In view of the negative impact of component importance measures based on system reliability theory and centrality measures based on complex networks theory, there is an attempt to provide improved centrality measures (ICMs) construction method with fuzzy integral for measuring the importance of components in electromechanical systems in this paper. ICMs are the meaningful extension of centrality measures and component importance measures, which consider influences on function and topology between components to increase importance measures usefulness. Our work makes two important contributions. First, we propose a novel integration method of component importance measures to define ICMs based on Choquet integral. Second, a meaningful fuzzy integral is first brought into the construction comprehensive measure by fusion multi-ICMs and then identification of important components which could give consideration to the function of components and topological structure of the whole system. In addition, the construction method of ICMs and comprehensive measure by integration multi-CIMs based on fuzzy integral are illustrated with a holistic topological network of bogie system that consists of 35 components.

1. Introduction

Recent decades have witnessed not only the rapid development on the highly integrated system of electromechanical systems, but also the significant progress on the system function [1]. Complex electromechanical systems, such as high-speed train, aircraft, and other large equipment, are composed of components with specific functions, physical and chemical connections, and behaviors, and coupled relationship through mechanic, electric, and information relationship. Due to the complexity of topological structure and functional relationship within electromechanical systems, one of the component's failures may lead to another component's failure, which is called fault propagation. The fault propagation of complex electromechanical systems can enlarge the negative impact due to one of components failures. In these situations, it is becoming increasingly important to take functional and topological characteristics into account when assessing the importance of components and concentrating the resources on the small subset of components that are most important to the system.

1.1. Previous Work. In system reliability theory, importance measures are used as effective tools to evaluate the relative importance of components and identify system weaknesses [2]. Component importance measures (CIMs) are component related indices that allow security practitioners to identify how a components fault affects the overall behavior or performance of the whole technological system and are used to evaluate the relative importance of a component. The typical CIMs include but are not limited to Birnbaum importance measure [3], Fussell-Vesely (FV) importance measure [4], and criticality importance measure [5]. Detailed descriptions and mathematical expressions for importance measures can be found in Ramirez-Marquez [6]. Using the CIMs, security practitioners can estimate or prioritize components in order of their importance value with regard to system reliability and concentrate maintenance resources on the most important components.

Recent advances indicate that electromechanical systems can be virtually represented as networks, where the components of technological products are easily depicted by the nodes of complex networks and the connections between linkage components are naturally depicted by the links of complex networks [7–9]. More recently, various centrality measures (CMs) have been presented to quantify the importance of an individual in a complex network, including degree centrality (DC) [10], betweenness centrality (BC) [11], and eigenvector centrality (EC) [12]. The issue of centrality has attracted the attention of physicists, who have been extending its applications to the realm of technological networks. For example, Dan et al. [13] considered that system networked reflected the organization structure and enhanced efficiency and capability of system development and production, and, in Li et al. [14] view, these physical connections between components determine the function and structure complexity of technological products. Based on CMs of complex network, Jiang et al. [15] introduced the loads and vulnerability coefficient of nodes to study the inherent vulnerability of components and Xu et al. [16] developed a comprehensive vulnerability index to find the vulnerable structure of complex system with a network model. Meanwhile, Zong et al. [17] regarded the node betweenness and node agglomeration as the indices to evaluate the importance of the components based on the maintenance relationship network.

However, all these researches focused on only one measure, such as component importance measure and one centrality measure, and every measure has its own disadvantage and limitation. In recent years, researchers study a multiattribute ranking problem to evaluate the component importance comprehensively from more than one perspective, which would be a special case of multicriteria decision-making (MCDM). MCDM refers to making decision for alternatives in the presence of multiple and conflicting criteria [18] and has many developments and applications, such as extensions of TOPSIS [19, 20], Analytic Hierarchy Process [21], K-shell decomposition [22], and entropy theory [23]. Detailed descriptions and mathematical expressions for multicriteria decision-making approaches can be found in Govindan et al. [24].

1.2. Problem Description. Although the above component importance measures or centrality measures have been widely applied in identifying influential components, there are some limitations and disadvantages. CIMs are built on the assumption of the independence of components and none of them has taken the impact of topological structure between components into account. CMs mentioned above focus only on the components propagation behavior of complex network and are limited to the point of the reliability analysis [25]. For these reasons, it is extremely important to research on the negative impact of these restrictions and proactively overcome them by complementation with elaborate reliability contexts on identifying influential components of electromechanical system. That is to say that CIMs or CMs cannot be applied to complex electromechanical systems that contain multiple components.

If only one measure is adopted, then the rankings of identifying influential components may be different by using a different measure. In some cases, using different centrality measures may provide different results, even conflicting results [26]. MCDM has been proposed to address this problem. However, the inherent limitations and disadvantages of CIMs or CMs cannot be eliminated through integration multimeasures. Moreover, among numerous MCDM methods developed to solve real-world decision problems, fuzzy integral continues to work satisfactorily across different application areas. The weights in most developments and applications of MCDM are determined in advance, such as TOPSIS and AHP, which possess definite subjectivity. Fuzzy integral makes full use of attribute information, provides a cardinal ranking of alternatives, reduces subjective influences, and does not require attribute preferences to be independent. As a well-known classical MCDM method, fuzzy integral has received much interest from researchers and practitioners.

In this paper, we try to introduce fuzzy integral theory to explore how to identify influential components. Our work makes two important contributions. First, we integrate component importance measures and centrality measures with Choquet integral to define a new kind of improved centrality measures. Second, a novel index, comprehensive measure, of a meaningful fuzzy integral-based is brought into identification of important components for which it could give consideration to function of components and topological structure of the whole system.

The rest of the paper is structured as follows. Section 2 provides background information about the holistic topological network and fuzzy integral theory. In Section 3, the improved centrality measures are detailed. The following is presented: how to improve centrality measures, by using Choquet integral to express functional and topological properties which are related, measuring the importance of components in electromechanical systems. In Section 4, we embed the fuzzy integral into the process of construction comprehensive measure and identification of critical components by fusing multi-improved centrality measures. Section 5 presents a case study which constructs improved centrality measures of bogie system and discusses the advantages of fusion improved centrality measures in identifying critical components based on fuzzy integral.

2. Methodological Background

2.1. The Holistic Topological Network. Currently, complex networks are being studied in many fields of science, such as social sciences, computer sciences, physics, biology, and economics. The majority of systems in reality can be undoubtedly described by models of complex networks. For example, Internet is a complex network composed of web sites [27, 28]. The brain is a complex network of neurons [29]. An organization is a complex network of people [30].

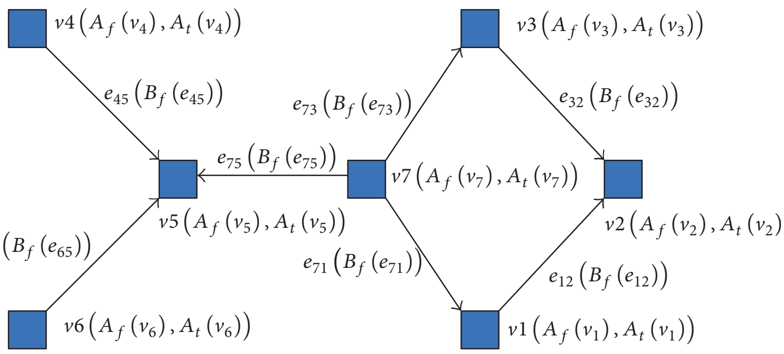

FIGURE 1: The holistic topological network.

As mentioned above, electromechanical systems are characterized by large scale, complex structure, nonlinear behavior, various working states, high coupling components, random operation environment, and so forth, which are not easy to be modeled directly to analyze global behaviors. Recently, lots of attempts have been made to model network in engineering, more specifically, electromechanical systems. It can be a complex network, in which the components are depicted by nodes and the physical connections between linkage components are depicted by links between the corresponding nodes. We refer to this representation as a topological structure and a formal model is presented by the following definitions.

We define HTN $= \langle V, E, f(V), f(E)\rangle$ as a *holistic topological network*

$$\begin{gathered} \text{HTN} = \langle V, E, f(V), f(E)\rangle \\ v_i \in V,\ e_{ij} \in E,\ f(v_i) = \{A_f(v_i), A_t(v_i)\} \subset f(V),\ f(e_{ij}) = \{B_f(e_{ij})\} \subset f(E),\ i = 1,\ldots,n;\ j \leq n, \end{gathered} \tag{1}$$

where $V = \{v_1, v_2, \ldots, v_n\}$ is a set of nodes and each node represents a component. n is the number of nodes. For example, the number of nodes is 7 for a system in Figure 1. $E = \{e_{ij} \mid i = 1,\ldots,n, j \in n\}$ is a set of links and e_{ij} represents physical connection between nodes v_i and v_j. Depending on the nature or type of the topological property, this property may be reflexive in that $e_{ij} \neq e_{ji}$. $f(V)$ is the properties of the set of nodes, $A_f(v_i)$ is the functional properties of v_i, and $A_t(v_i)$ is the topological properties of v_i. $f(E)$ is the properties of the set of edges and $B_f(e_{ij})$ is the functional properties of edge e_{ij}.

For different systems, the properties of nodes or edges may be also different. For instant, assuming that Figure 1 is the partial bogie system of CRHX, the properties of nodes and edges in the *holistic topological network* are as follows.

(1) $A_f(v_i) = \{\mathrm{LT}_i, \mathrm{MTBF}_i, \lambda_i\}$. LT_i is the service life of node v_i, which is its expected lifetime or the acceptable period of use in service. It is the time that any manufactured item can be expected to be "serviceable" or supported by its manufacturer. We can obtain this parameter from its manufacturer.

λ_i is failure rate of node v_i and is defined as

$$\lambda_i(t) = \lim_{\Delta t \to 0} \frac{R_i(t) - R_i(t + \Delta t)}{\Delta t \cdot R_i(t)}, \tag{2}$$

where $R_i(t)$ is the probability of no failure before time t for node v_i; Δt is the over-a-time-interval from failure time t to the next failure time. In this paper, failure rate λ_i depending on failure data is computed.

MTBF_i is mean time between failures of node v_i and the formula is

$$\mathrm{MTBF}_i = \frac{\sum \left(f_i^d - f_i^u\right)}{N_i^f}, \tag{3}$$

where f_i^d is start of downtime for node v_i, f_i^u is start of uptime for node v_i, and N_i^f is the number of failures.

(2) $A_t(v_i) = \{\mathrm{BC}_i, \mathrm{CC}_i, \mathrm{DC}_i, \mathrm{EC}_i\}$. CC_i is closeness centrality [31] of node v_i:

$$\mathrm{CC}_i = \frac{1}{\sum_j^n d_{ij}}, \tag{4}$$

where d_{ij} denotes the distance between node v_i and node v_j; n is the number of nodes.

BC_i is betweenness centrality [31] of node v_i:

$$\mathrm{BC}_i = \sum_{j,k \neq i} \frac{g_{jk}(i)}{g_{jk}}, \tag{5}$$

where g_{jk} is the number of binary shortest paths between node v_j and node v_k and $g_{jk}(i)$ is the number of those paths that go through node v_i.

DC_i is degree centrality [32] of node v_i:

$$\mathrm{DC}_i = \sum_{j}^{N} x_{ij}, \tag{6}$$

where i is the focal node v_i; j represents all other nodes; N is the total number of nodes; x_{ij} represents the connection between node v_i and node v_j. The value of x_{ij} is defined as 1 if node v_i is connected to node v_j and 0 otherwise.

EC_i is eigenvector centrality [12] of node v_i. Let A be a $n \times n$ similarity matrix. The eigenvector centrality EC_i of node v_i is defined as the ith entry in the normalized eigenvector belonging to the largest eigenvalue of A. λ is the largest eigenvalue of A and n is the number of vertices:

$$\begin{gathered} A \cdot \mathrm{EC} = \lambda \cdot \mathrm{EC} \\ \mathrm{EC}_i = \mu \sum_{j=1}^{n} a_{ij} \mathrm{EC}_j, \quad i = 1, \ldots, n \end{gathered} \tag{7}$$

with proportionality factor $\mu = 1/\lambda$ so that EC_i is proportional to the sum of similarity scores of all nodes connected to it.

(3) $B_f(e_{ij}) = \{p_{ij}, \mathrm{st}_{ij}, \lambda_{ij}\}$. p_{ij} is fault propagation probability of edge e_{ij}, given by

$$p_{ij} = \frac{l(e_{ij})}{\sum_{i \neq j} l(e_{ij})}, \tag{8}$$

where $l(e_{ij})$ is the number of shortest paths crossing a given edge e_{ij}. Gao et al. [33] introduced the concept and computational method of fault propagation probability in detail.

st_{ij} is connection strength of edge e_{ij} and is given by [34, 35]

$$\mathrm{st}_{ij} = \beta \frac{s(v_i \mid v_j)}{s(v_i)}, \tag{9}$$

where $s(v_i)$ is the number of times that operation states change in the statistical time; $s(v_i \mid v_j)$ indicates the number of times that v_i operation states change arising from v_i in the statistical time. The operation states of v_i contain the failure mode and normal operation mode of the corresponding component. β is an empirical contact duration of the type of functional dependencies between components v_i and v_j.

λ_{ij} is failure rate of edge e_{ij}. The calculation method is the same as the failure rate of node in (2).

In Figure 1, the edge describes the physical connection between linkage components, and the arrow of the edges expresses the failure interaction of nodes. Liu and An [22] further introduced how to determine the direction of edges which describe the coupling relation of the failure interactions.

2.2. Fuzzy Integral Theory. About thirty years ago the concept of fuzzy integral was proposed in Japan by Sugeno [36, 37], which in the discrete case is merely a kind of distorted mean. Although this was followed by a rather mathematically oriented research, far from application concerns, some Japanese researchers, including Sugeno himself, thought that fuzzy integrals could be applied to multicriteria evaluation: since 1985, papers have been published on supplier evaluation and improvement [38], analysis of policy decision of sustainable energy strategies [39], fusion of extreme learning machine [40], analysis of human reliability [41], and so forth. The distinguishing feature of fuzzy integral is that it is able to represent a certain kind of interaction between criteria, ranging from redundancy (negative interaction) to synergy (positive interaction). To our knowledge, there is almost no well-established method to deal with interacting criteria, and usually people tend to avoid the problem by constructing independent (or supposed to be so) criteria. This innovative feature was without any doubt the reason of its success in various fields of application [42]. A wide variety of forms have been presented for fuzzy integral, such as Choquet integral [43] and Sugeno integral.

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a nonnull and finite set of attributes or influence factors and let $P(X)$ denote the power set of X.

2.2.1. Discrete Choquet Integral. Let g_λ be a λ fuzzy measure in $P(X)$. The discrete Choquet integral of an element $f : X \to IR^+$ with respect to g_λ is defined by

$$(c) \int f \, dg_\lambda = \sum_{i=1}^{n} \left(f\left(x_{(i)}\right) - f\left(x_{(i-1)}\right) \right) g_\lambda \left(A_{(i)}\right), \tag{10}$$

where (i) indicates a permutation on X such that $f(x_{(1)}) \leq \cdots \leq f(x_{(n)})$. Also $A_{(i)} = (x_{(i)}, \ldots, x_{(n)})$ is an attribute set, and $f(x_{(0)}) = 0$. Discrete Choquet integral is the extension of the weighted average operator, which considers the relationships among attributes or influence factors.

2.2.2. Discrete Sugeno Integral. Let μ be a fuzzy measure on X and $f : X \to [0, 1]$ be a function. The discrete Sugeno integral of f with respect to μ is

$$(s) \int f \, d\mu = \bigvee_{i=1}^{n} \left(f\left(x_{(i)}\right) \wedge \mu\left(A_{(i)}\right) \right), \tag{11}$$

where $0 \leq f(x_{(i)}) \leq f(x_{(2)}) \leq \cdots \leq f(x_{(n)}) \leq 1$, $A_{(i)} = (x_{(i)}, x_{(i+1)}, \ldots, x_{(n)})$ is an attribute set and $f(x_{(0)}) = 0$.

3. Improved Centrality Measures

In this section, the novel importance measures, that is, improved centrality measures (ICMs), are first proposed. It is a series of special importance measures to find the influential components that are really crucial for the normal operation of electromechanical systems. When some components lose or weaken their functions due to a certain mode of failures, there will be a degradation of the holistic system performance. Based on centrality measures, the originality and novelty of proposed ICMs is that they evaluate the importance of a

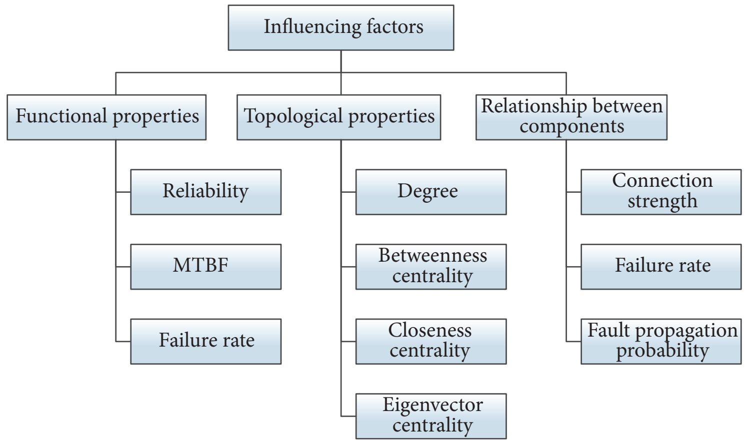

Figure 2: Influencing factors of the individual components.

component by taking into account the functional and topological properties in the holistic system. In essence, they are comprehensive indicators in the system, which are proposed for the assessment of the most important component.

3.1. Influencing Factors. In order to measure the importance of components, influential factors that are capable of representing the desired function of the individual components, as well as their structure, are required. Some quantitative information is introduced into the system to improve the accuracy of the important measure of the components. For example, functional properties reflect the ability of the system to perform its intended function, and topological properties describe the stability of the inherent structure of the system.

Through the project (*The National High Technology Research and Development Program of China (863 Program)* number 2012AA112001) of cooperation with *CRRC Corporation Limited*, we have discussed with engineers and maintenance personnel in detail and then obtained the influential factors of bogie system as shown in Figure 2, which include the functional properties, which are used to depict the system performance, and the topological properties, which are used to describe the influence on system structure.

3.2. Improved Centrality Measures. A large number of centrality measures have been proposed to identify influential nodes within a complex network. Examples are DC, CC, BC, and EC. However, it cannot be ignored that while most of these centrality measures have been widely used in *Network Reliability Analysis*, challenges still remain in regard to the following: none of them has taken into account the impact of functional influences of nodes and edges in the holistic topological network.

Improved centrality measures are a series of importance measures which are extended from centrality measures. In a sense, ICMs can serve as better importance measures of components, as it synthesizes the components functional properties, such as usage reliability, failure rate, and connection strength, meanwhile, by taking systems structure into account, such as CC, BC, DC, and EC.

The following is an efficient and universal construction method to calculate ICMs.

Let us consider $A_f(v_i)$ in (1), which consists of functional properties of nodes, $A_t(v_i)$, which consists of topological properties of nodes, and $B_f(e_{ij})$, which consists of functional properties of edges.

Based on the holistic topological network, functional properties of nodes and edges are integrated into the definition of centrality measures, and then ICMs are constructed, defined as follows:

$$\begin{aligned} \mathrm{ICM}_s(i) = (c)\int\Big(x_s(i), (c)\int A_f(i)\, d\mu_{A_f}, (c) \\ \cdot \int B_f(e_{ij})\, d\mu_{B_f}\Big)\, d\mu_{\mathrm{ICM}} \\ x_s(i) \in A_t(i), \end{aligned} \tag{12}$$

where $\mathrm{ICM}_s(i)$ is the improved centrality measure of node v_i. μ is the weight of influencing factors.

According to (12), the first thing that we need is to calculate weight μ. Here, we use g fuzzy measure and k additive fuzzy measure to compute weight μ based on Shapley values [44] and Marichal entropy theory [45]. The maximum Marichal entropy as the objective function constructs optimization model as shown in (13) based on fuzzy theory. And then, calculating (13), we can get the parameter μ.

$$\begin{aligned} \max_{\lambda,\mu} \quad & H_M(\mu) = \sum_{i=1}^{n} \sum_{S\subseteq A-a_i} \gamma_s[n]\cdot h\left[\mu(S\cup a_i) - \mu(S)\right] \\ \text{s.t.} \quad & I_i \\ & = \sum_{k=0}^{n-1} \frac{(n-k-1)!k!}{n!} \sum_{T\subseteq A-a_i, |T|=k} \left(\mu(T\cup a_i) - \mu(T)\right) \\ & \mu(A) = 1 \end{aligned}$$

$$\begin{aligned}
&\mu(M \cup N) = \mu(M) + \mu(N) + \lambda\mu(M)\mu(N) \\
&\qquad\qquad \forall M, N \in P(A), M \cap N = \phi \\
&\mu(M) \in [0,1] \quad \forall M \in P(A) \\
&\lambda \in (-1, \infty) \\
&i = 1, \ldots, n.
\end{aligned} \tag{13}$$

Zhang et al. [39] explained all the parameters in (13) and introduced the calculation methods in detail.

Some simple examples are given to explain how ICMs perform.

3.2.1. Improved Degree Centrality (IDC). In a binary network, DC_i of node v_i represents the total number of the connection with node v_i. However, functional properties of edges, which connect with node v_i and node v_i cannot be ignored. The improved degree centrality, denoted as IDC_i, is given by

$$\begin{aligned}
&T_{t=1,\ldots,N_i}(e_{ij}) = (c)\int B_f(e_{ij})\,d\mu(H_{e_{ij}}), \\
&\qquad \text{if } a_{ij} = 1,\ \text{exist } e_{ij};\ \text{else no exist } e_{ij} \\
&H_1 = (c)\int (T_1, \ldots, T_{N_i})\,d\mu(H_T) \\
&H_2 = (c)\int A_f(v_i)\,d\mu(H_v) \\
&\mathrm{IDC}_i = (c)\int (\mathrm{DC}_i, H_1, H_2)\,d\mu(H),
\end{aligned} \tag{14}$$

where $T_t(e_{ij})$ is the aggregate value of functional properties of edge e_{ij}, which is connected to v_i. The value of a_{ij} is defined as 1 if node v_i is connected to v_j, and 0 otherwise. H_1 is the aggregate value of functional properties of all edges which are connected to v_i. H_2 is the aggregate value of functional properties of node v_i. μ is the weight of influencing factors.

3.2.2. Improved Closeness Centrality (ICC). The improved closeness centrality of node v_i, denoted as ICC_i, is defined as

$$\mathrm{ICC}_i = \left[\sum_{j}^{N} \mathrm{ISP}_{ij}\right]^{-1}, \tag{15}$$

where ISP_{ij} is the improved shortest path between nodes v_i and v_j. Its definition and calculation are explained as follows.

Given a directed graph, the length of a path is the number of edges forming it. We define the shortest path as the smallest length among all the paths connecting the source vertex to the target vertex. However, for electromechanical systems, functional properties of nodes and edges also can influence the length of the shortest path. Given that $V_{l_i}^{e_{st}}$ represents a set of nodes, which are in l_ith path from node v_s to node v_t, and $E_{l_i}^{e_{st}}$ represents a set of edges, which are in l_ith path from node v_s to node v_t, improved shortest path can be expressed as follows:

$$\begin{aligned}
\mathrm{ISP}_{ij} = \min_{l_i} \quad & (c)\int \{d_{ij}, Y_{l_i}(v), Y_{l_i}(e)\}\,d\mu(H_{l_i}) \\
\text{s.t.} \quad & W_{l_i}^{e_{st}}(v_j) = (c)\int A_f(v_j)\,d\mu(H_{v_j}), \\
& \qquad v_j \in V_{l_i}^{e_{st}} \\
& W_{l_i}^{e_{st}}(e_{pq}) = (c)\int A_f(e_{pq})\,d\mu(H_{e_{pq}}), \\
& \qquad e_{pq} \in E_{l_i}^{e_{st}} \\
& Y_{l_i}(v) = (c)\int \{W_{l_i}^{e_{st}}(v_j)\}\,d\mu(H_{W_{l_i}(v)}), \\
& \qquad v_j \in V_{l_i}^{e_{st}} \\
& Y_{l_i}(e) \\
& \quad = (c)\int \{W_{l_i}^{e_{st}}(e_{pq})\}\,d\mu(H_{W_{l_i}(e)}), \\
& \qquad e_{pq} \in E_{l_i}^{e_{st}},
\end{aligned} \tag{16}$$

where $W_{l_i}^{e_{st}}(v_j)$ is the aggregate value of functional properties of node v_j which is in path l_i; $W_{l_i}^{e_{st}}(e_{pq})$ is the aggregate value of functional properties of edge e_{pq} which is in path l_i; $Y_{l_i}(v)$ is the aggregate value of $W_{l_i}^{e_{st}}(v_j)$ which is in path l_i; $Y_{l_i}(e)$ is the aggregate value of $W_{l_i}^{e_{st}}(e_{pq})$ which is in path l_i.

3.2.3. Improved Betweenness Centrality (IBC). The improved betweenness centrality of node v_i, denoted as IBC_i, can be rewritten as

$$\mathrm{IBC}_i = \sum_{j,k \neq i} \frac{\mathrm{ISP}_{jk}(v_i)}{\mathrm{ISP}_{jk}}, \tag{17}$$

where ISP_{jk} is the improved shortest path between nodes v_j and v_k; $\mathrm{ISP}_{jk}(v_i)$ is the number of those paths that go through node v_i.

4. Proposed Method

The ICMs, such as IDC, ICC, and IBC, reflect the function and structure of system from one aspect and cannot comprehensively reflect the functional and topological characteristics. In some cases, the results of IDC and ICC may be different, even conflicting results. To address this issue, in this paper, comprehensive measure is introduced firstly to explore how to fuse multi-ICMs based on fuzzy integral and then identify influential components. As a well-known fuzzy integral theory, Sugeno integral and Choquet integral have received much interest from researchers and practitioners.

Let us consider a decision matrix $D_m = (\mathrm{ICM}_{mn})$, where ICM_{mn} is the nth improved centrality measure of node v_m.

If we choose Sugeno integral, the comprehensive measure of node v_i, denoted as IS_i, is defined as follows:

$$\mathrm{IS}_i = (s)\int D_i d\mu = \bigvee_{j=1}^{m}\left(\mathrm{ICM}_{i(j)} \wedge \mu\left(A_{i(j)}\right)\right), \quad i = 1, \ldots, n. \tag{18}$$

If we choose Choquet integral, the comprehensive measure of node v_i, denoted as IC_i, is defined as follows:

$$\mathrm{IC}_i = (c)\int D_i d\mu = \sum_{j=1}^{m}\left(\mathrm{ICM}_{i(j)} - \mathrm{ICM}_{i(j-1)}\right)\mu\left(A_{i(j)}\right), \quad i = 1, \ldots, n, \tag{19}$$

where $A_{i(j)} = (\mathrm{ICM}_{i(1)}, \ldots, \mathrm{ICM}_{i(N)})$ and $\mu(A_{i(j)})$ is the weight for improved centrality measure.

The specific steps of the method are illustrated as follows.

Step 1 (construct the holistic topological network of complex electromechanical system). We can construct a network based on Section 2.1. The components are abstracted as nodes, and the connections between components are represented as edges. And then the system can be described as a network.

Step 2 (calculate properties value of nodes and edges). According to Figure 2, we compute the properties of nodes and edges in combination failure data. The attributes of nodes are obtained by (2)~(7), and properties of nodes are computed by (8).

Step 3 (construct and calculate the improved centrality measures by (12)). In this step, we apply (12) to construct and calculate the different improved centrality measures, such as improved degree centrality, improved closeness centrality, and improved betweenness centrality.

Step 4 (select fuzzy integral and fuse all improved centrality measures by (18) or (19)). The alternatives with higher IC_i or IS_i are assumed to be more important and should be given higher priority. Finally, the influence of the node is identified by the value IC_i or IS_i.

The flow chart of the proposed methods is shown in Figure 3.

5. A Case Study and Discussion

China Railway CRHX Size (CRHX) is designed for a speed of 350 km/h and each car is suspended by two bogies. The bogie system of the 350 km/h EMU train is one of the key parts of CRHX which plays an important role in sustaining the static load from the body weight of a car, carrying the suspensions, brakes, wheels, and axles and controlling wheel sets on curved and straight tracks, in accordance with Figure 4. The bogie system can be highly complex due to the systematic use of new technologies and be functional relationship due to the interactions among components. With rapid increase of EMU train speed, the behavior of bogie system becomes more dynamic and uncertain, which not only affects the ride comfort of passengers but also directly relates to the reliability and safety of the train. Generally, the operation of the bogie system depends on 35 components, in accordance with Table 1.

Table 1: Components in bogie system.

Number	Name
v_1	Bogie frame
v_2	Brake Caliper
v_3	Brake lining
v_4	Brake discs
v_5	Booster cylinder
v_6	Spring
v_7	Axle box body
v_8	Vertical shock absorber
v_9	Bearing
v_{10}	Wheel
v_{11}	Axle
v_{12}	Secondary vertical shock absorber
v_{13}	Railway coupling
v_{14}	Gearbox
v_{15}	Grounding device
v_{16}	Traction motor
v_{17}	Height adjusting device
v_{18}	Antihunting damper
v_{19}	Air spring
v_{20}	Center pin bush
v_{21}	Traction rod
v_{22}	Transverse shock absorber
v_{23}	Transverse backstop
v_{24}	Anti-side-rolling torsion bar
v_{25}	Control valve
v_{26}	Speed Sensor 1
v_{27}	Speed Sensor 2
v_{28}	LKJ2000
v_{29}	Device for cleaning the tread band of vehicle wheels
v_{30}	Acceleration sensor
v_{31}	Junction box
v_{32}	Temperature sensor bearing
v_{33}	Axle temperature sensor
v_{34}	AG37
v_{35}	AG43

5.1. The Network Model and Related Data. In this section, a case concerning the holistic topological network model of bogie system (as shown in Figure 5) is established as a decision support tool for importance measures and safety assurance, to provide effective support for decision-makers to

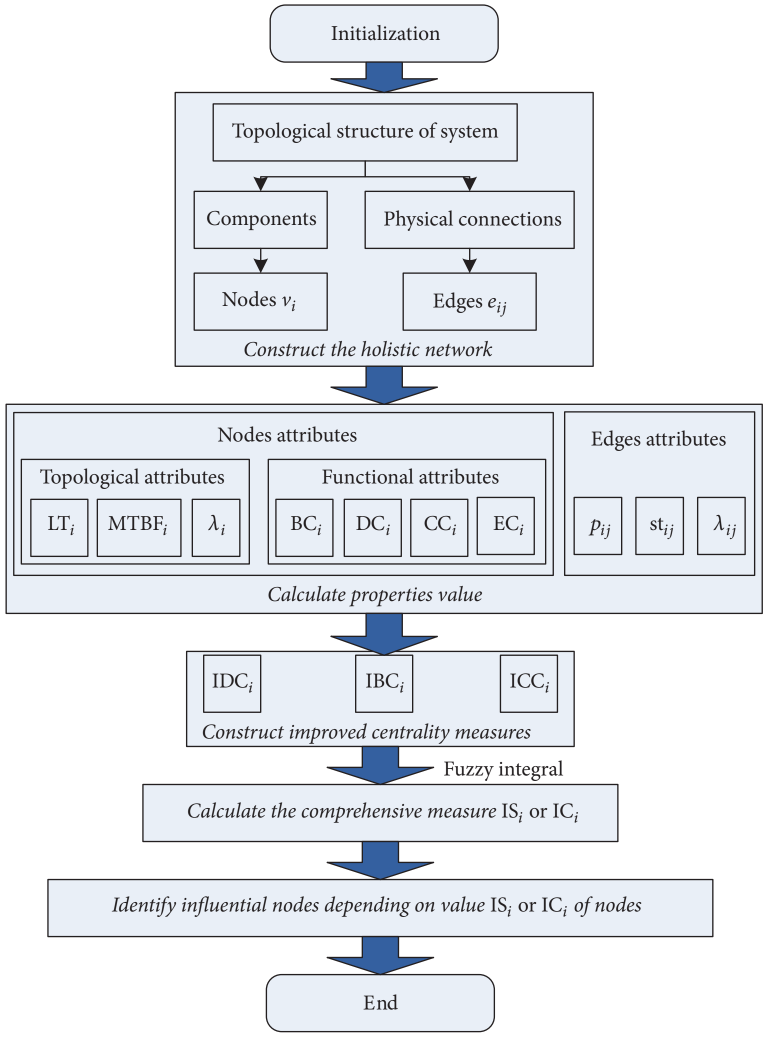

FIGURE 3: The flow chart of the proposed method.

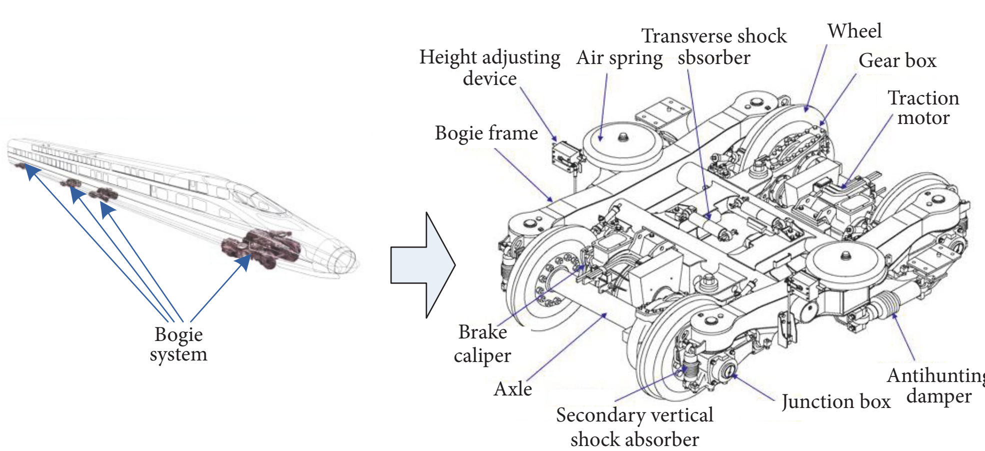

FIGURE 4: Structural features of bogie system.

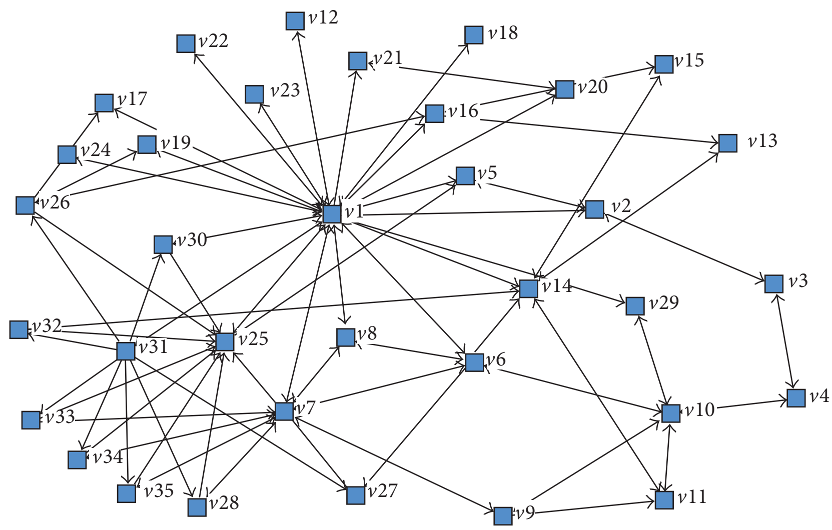

Figure 5: The holistic topological network of bogie system: every node v_i has property set $(A_f(v_i), A_t(v_i))$, and every edge e_{ij} has property set $(B_f(e_{ij}))$.

proactively understand components interactions and assess their impact to the overall system. According to the construction method of network in Section 2.1, influential factors of bogie system in Figure 2, components of bogie system in Table 1, and the holistic topological network model of bogie system are described as follows:

$$\begin{gathered}\mathrm{HTM} = \langle V, E, f(V), f(E) \rangle \\ v_i \in V = \{v_1, v_2, \dots, v_{35}\}, \; e_{ij} \in E = \{e_{ij} \mid i, j \in 35\}, \; A_f(v_i) = \{\mathrm{MTBF}_i, \lambda_i, L_i\} \subset f(V), \; A_t(v_i) = \{\mathrm{DC}_i, \mathrm{BC}_i, \mathrm{CC}_i, \mathrm{EC}_i\} \subset f(V), \; B_f(e_{ij}) = \{\mathrm{st}_{ij}, \lambda_{ij}, p_{ij}\} \subset f(E).\end{gathered} \tag{20}$$

The attributes of edges and nodes in (20) are calculated according to the equation in Section 2.1. Related data, which is necessary for calculation, can be collected from historical failure databases and expert elicitation. For high-speed train system, through a project of cooperation with CRRC Corporation Limited, we have obtained the historical failure databases of CRHX during 2009 to 2014 (863 Program number 2012AA112001). In these databases, each failure data record contains the failure ID numbers, the vehicle ID number, the section of failure, the failure mode, the date of failure, the environment of failure, and so forth. We deal with the data by removing some irrelevant items. However, these data cannot be directly used to compute properties and need to be preprocessed. And, a preprocessed failure data of gear box in bogie system is presented in Table 2.

Using the preprocessed failure data of CRHX and (2)~(3), this paper estimates the parameters for possible faults distribution function. Based on the faults distributing functions and the necessary correction, we can obtain components' failure rate and MTBF. The nodes failure rate and MTBF within 120 million kilometers and service life time are shown in Table 3.

Edges have a striking effect on critical nodes in the network. In essence, edges in holistic topological network also describe components, but these components have different properties from nodes. The fault propagation probability, connection strength, and failure rate of edges are computed according to (2), (8), and (9) based on failure date and shown as in Table 4.

5.2. ICMs for Bogie System. CMs of nodes in the holistic topological network are necessary to construct improved centrality measures to assess influential components. According to (20) and complex network theory, we can obtain centrality measures of all nodes, such as BC, CC, DC, and EC in (4)~(7). Figure 6 shows the results of CMs in the network. We can see that node v_1 has the highest BC, CC, DC, and EC, and it means that the most important node in the holistic topological network of a bogie system is *bogie frame* (the corresponding node is v_1). This is consistent with the structural status of the bogie frame in the bogie system.

In the method proposed in this paper, the assessment of influential components requires, firstly, exhaustive and systematic definition and calculation improved centrality measures for any given number of components according to Section 3.2. Figure 7 is presented to demonstrate the calculation results of ICMs by combination with CMs in Figure 5 and functional properties of nodes and edges in Tables 3 and 4. From Figure 7, we can also obtain that bogie frame (the corresponding node is v_1) is identified as the most important components, which is in line with practical experience.

In order to explain the advantages of ICMs, we compare with the identification results of ICMs and CMs. The most

Table 2: The preprocessed failure data of gear box.

Number	Mileage/10^5 km	Failure mode
(1)	6.39853	Oil leakage
(2)	7.87662	Oil leakage
(3)	7.90238	Gear shift
(4)	10.02856	Oil leakage
(5)	11.26585	Crackle
(6)	11.29788	Oil leakage
(7)	12.39568	Oil leakage
(8)	14.02572	Crackle
(9)	15.64292	Crackle
(10)	16.39853	Oil leakage
(11)	16.64292	Crackle
(12)	16. 64292	Oil leakage
(13)	17.66824	Oil leakage
(14)	18.16762	Gear shift
(15)	18.2579	Oil leakage
(16)	19.32587	Gear shift
(17)	19.90225	Oil leakage
(18)	21.0191	Crackle
(19)	22.17948	Crackle
(20)	22.38788	Crackle
(21)	23.0191	Oil leakage
(22)	27.73312	Oil leakage
(23)	28.62366	Crackle
(24)	28.87598	Oil leakage
(25)	29.62366	Oil leakage
(26)	31.79775	Crackle
(27)	32.4842	Crackle
(28)	33.43831	Crackle
(29)	34.43831	Gear shift
(30)	34.50838	Crackle
(31)	37.66297	Oil leakage
(32)	38.66297	Gear shift
(33)	40.0016	Crackle

Table 3: The nodes functional properties.

Node	Life time/year	Failure rate	MTBF
v_1	20	0.0134	2.34
v_2	20	0.00798	1.25
v_3	15	0.0089	1.54
v_4	20	0.0045	2.21
v_5	20	0.0079	1.72
v_6	20	0.0059	1.92
v_7	20	0.0086	1.41
v_8	20	0.0081	1.69
v_9	20	0.0144	1.21
v_{10}	20	0.0126	1.34
v_{11}	20	0.0176	1.47
v_{12}	20	0.0079	1.65
v_{13}	20	0.0082	1.41
v_{14}	20	0.0103	1.52
v_{15}	20	0.0103	1.81
v_{16}	20	0.0078	1.45
v_{17}	20	0.0116	1.44
v_{18}	20	0.0082	1.66
v_{19}	15	0.0061	2.03
v_{20}	20	0.0052	1.55
v_{21}	20	0.0051	1.97
v_{22}	20	0.0062	1.86
v_{23}	20	0.0049	1.93
v_{24}	20	0.0051	1.77
v_{25}	20	0.0072	1.78
v_{26}	20	0.0077	1.68
v_{27}	20	0.0177	1.32
v_{28}	20	0.0187	1.43
v_{29}	20	0.0107	1.50
v_{30}	20	0.0152	1.41
v_{31}	20	0.0049	1.53
v_{32}	20	0.0165	1.32
v_{33}	15	0.0189	1.38
v_{34}	20	0.0191	1.49
v_{35}	20	0.0169	1.53

critical node in bogie system is all v_1. However, the importance ranking of other components is also the key to ensure system safety and reliability. In fact, maintenance personnel give more attention to a series of critical components, but not only the most important component. Figure 8 indicates the ranking of all nodes. We can clearly find that v_2, which is the identification result by using DC, is more important in network from a topological point of view. However, if we use improved DC to analyze the Brake Caliper, the result shows that Brake Caliper is not much more important than other nodes. This effect can be explained by the fact that ICMs of components are influenced by functional properties of nodes and edges that are linked to closer neighbors at the same time. Hence, with the functional influence of nodes and edges, the importance of nodes may change. Just as we have mentioned, ICMs is better than CMs.

Another interesting fact observed is that, as presented in Figure 8, the ranking of all nodes is different by using IBC, ICC, IDC, and IEC. Note that the result of IDC shows that v_1, traction motor v_{16}, and v_7 are the critical components. If we use ICC to identify influential components, the results reveal that v_1, v_7, and v_6 are the most important for bogie system. However, v_1, v_7, and v_{14} are the critical components by using IBC identification, and the identification results of IEC show that v_7, v_{25}, and v_{31} are essential for bogie system. This research presented two aspects of reasons for this: one is different influences which are taken into consideration and another is the uncertainty and randomness when single measure is used to identify critical component. For example, $DC_2 < IDC_2$; however, $CC_2 > ICC_2$; $DC_{15} < IDC_{15}$, but $BC_{15} > IBC_{15}$. CMs are constructed in which topological properties are taken into consideration, and ICMs are defined in combination with functional and topological features.

Table 4: Functional properties of several edges.

Edge	Connection strength	Failure rate	Fault propagation probability	Edge	Connection strength	Failure rate	Fault propagation probability
e_{12}	0.4	0.0051	0.0001	$e_{1,14}$	0.6	0.0068	0.0003
e_{13}	0.5	0.0087	0.0005	e_{51}	0.4	0.0053	0.0004
e_{15}	0.5	0.0095	0.0006	e_{61}	0.7	0.0071	0.0001
e_{16}	0.8	0.0088	0.0003	e_{52}	0.5	0.0067	0.0015
e_{17}	0.6	0.0082	0.0003	e_{67}	0.3	0.0104	0.0010
e_{18}	0.5	0.0062	0.0007	$e_{10,4}$	0.7	0.0045	0.0013
$e_{1,12}$	0.7	0.0079	0.0004	$e_{11,9}$	0.4	0.0042	0.0011
...	...	...	...	...	...	...	...

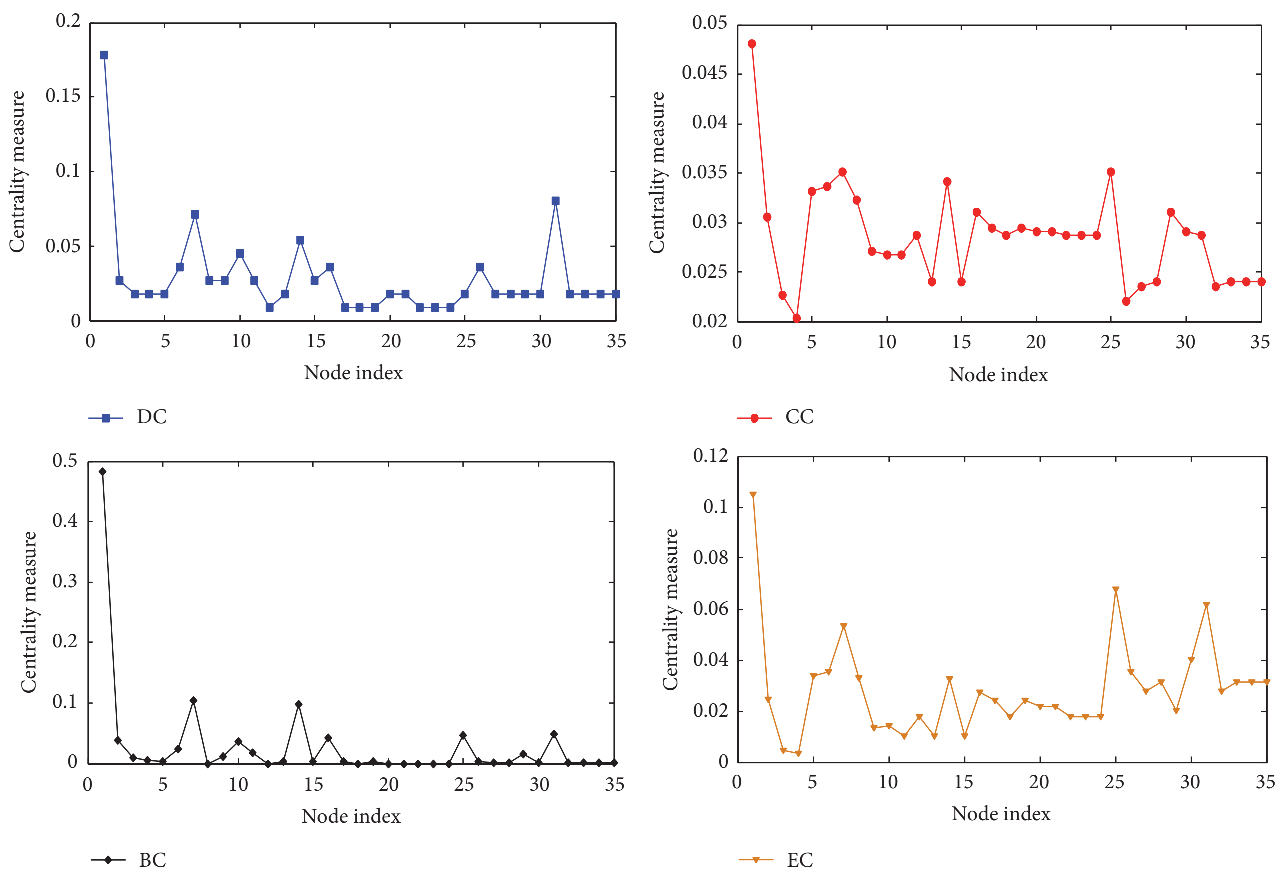

Figure 6: CMs of nodes in the holistic topological network.

5.3. Influential Components Based on Fuzzy Integral. In order to overcome the uncertainty and randomness which applies for single measure identifying critical component, we fuse ICMs to explore how to identify influential components based on fuzzy integral. According to Section 4, Figure 9 is described to demonstrate the result of comprehensive importance calculations. The result shows that the bogie frame and axle box body (the corresponding nodes are v_1, v_7) are identified as the most important components, which is in line with practical experience. The more critical nodes which are identified by Sugeno integral are the same as the Choquet integral. However, the calculation of Choquet integral is smaller than Sugeno integral and there is a problem that Sugeno integral will miss the information in calculation process. Therefore, the different integrals are selected based on different operation conditions when only more critical components need to be evaluated.

Meanwhile, how to calculate weight μ in fuzzy integral also is important for the accuracy of assessment results. The two methods are provided to compute weight μ, and

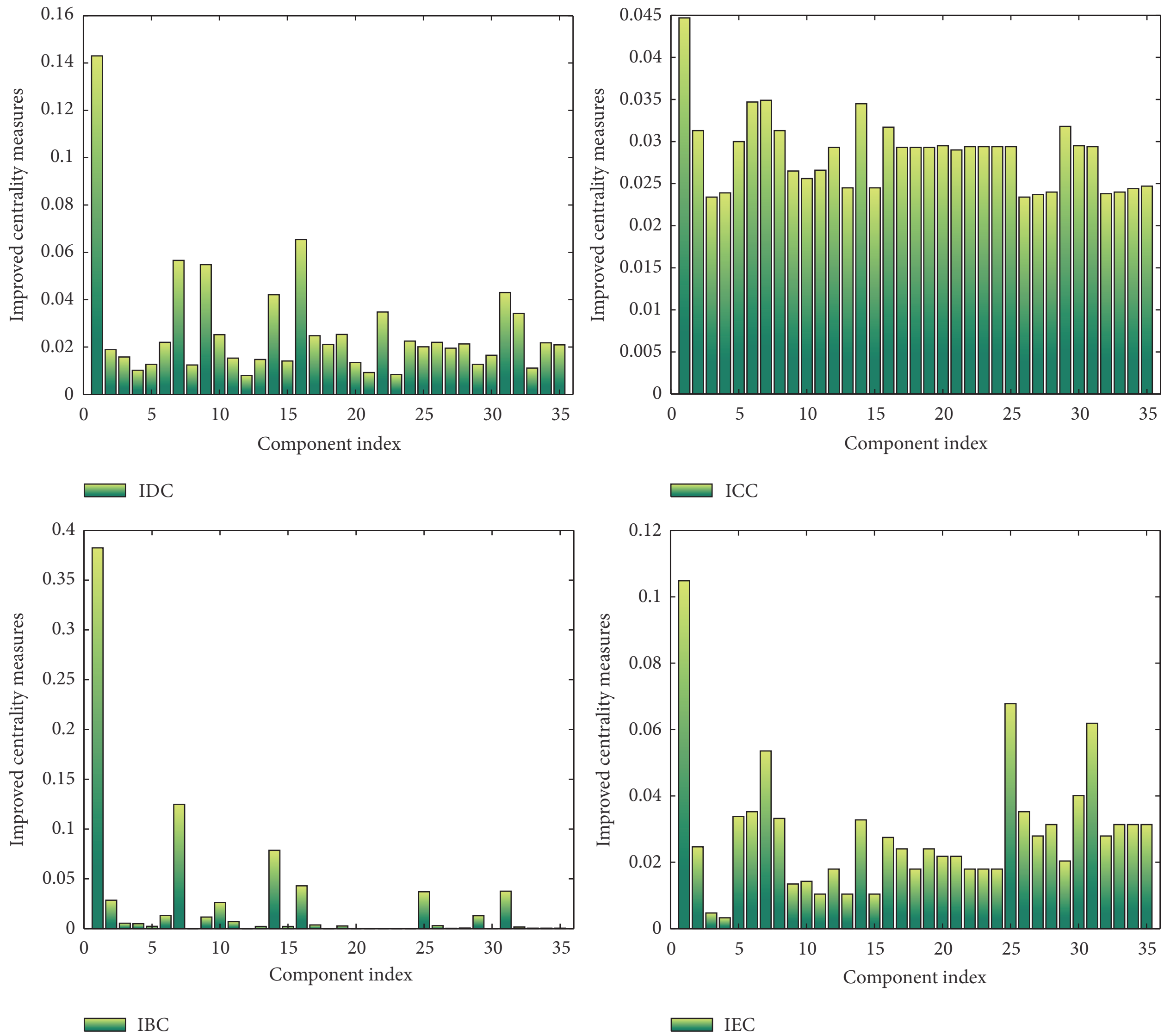

Figure 7: Improved centrality measures.

they are g fuzzy measure and k additive fuzzy measure. Theoretically, the accuracy of computation results based on k additive fuzzy measure is higher than g fuzzy measure. g fuzzy measure analyzes weights of all influences and their influencing relationship; however, k additive fuzzy measure provides weights of all influences and their influencing relationship for each nodes. Moreover, the application of k additive fuzzy measure is limited to the problem of large quantities of computation. Fortunately, we can find that most identification results with g fuzzy measure are the same as k additive fuzzy measure in Figure 9. Therefore, the g fuzzy measure can be chosen in traditional study.

5.4. Discussion. To better assess the importance of a component in the holistic topological network, the method of integration ICMs is proposed in this paper, which takes functional and topological properties into account. It is much different from integration topological CMs indicators such as DC, BC, CC, and EC mentioned in Section 5.2. From an experimental viewpoint, Figure 10 shows the results of integration CMs and ICMs. The ranking of all nodes by comprehensive measure, which is constructed by integration ICMs, is different from integration CMs. The weakness and shortage of CMs cannot disappear if we integrate CMs. Therefore, the accuracy of only integration CMs is still lower.

Table 5 presents the evaluation results of different methods. Based on *863 Program* (number 2012AA112001), we investigate the bogie system of CRHX in-depth, communicate with maintenance personnel, and attain the ranking of important components for using the enterprise, as shown in *Practical recognition* in Table 5. From the expert experience viewpoint, the most important nodes in the holistic topological network of a bogie system are v_1, v_7, v_{16}, and v_{14}, respectively. In the view of ICMs, these centrality measures

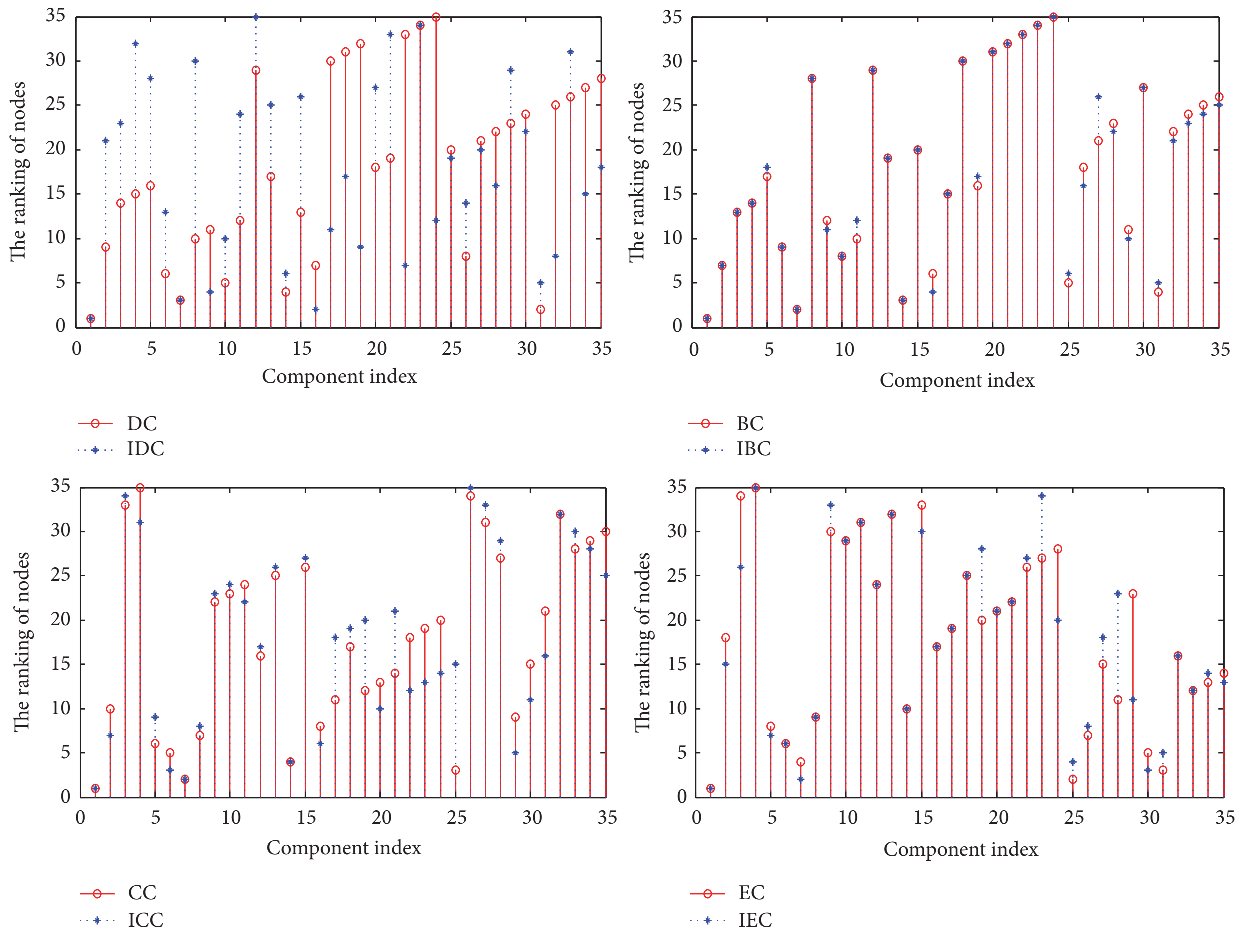

Figure 8: The ranking of nodes.

Table 5: The evaluation results of different methods.

Number	AHP	TOPSIS	DC	CC	BC	EC	Practical recognition	Sugeno integral		Choquet integral	
								g_λ	k-additive	g_λ	k-additive
(1)	v_1	v_1	v_1	v_1	v_1	v_1	v_1	v_1	v_1	v_1	v_1
(2)	v_{16}	v_7	v_{31}	v_7	v_7	v_{25}	v_7	v_7	v_7	v_7	v_7
(3)	v_{14}	v_{14}	v_7	v_{25}	v_{14}	v_{31}	v_{14}	v_6	v_{14}	v_{14}	v_{14}
(4)	v_{31}	v_9	v_{14}	v_{14}	v_{31}	v_7	v_{16}	v_{14}	v_{16}	v_{16}	v_{16}
(5)	v_7	v_{16}	v_{10}	v_6	v_{25}	v_{30}	v_{31}	v_{29}	v_{31}	v_9	v_9
(6)	v_9	v_8	v_6	v_5	v_{16}	v_6	v_9	v_{16}	v_{25}	v_{31}	v_{31}
(7)	v_{19}	v_{12}	v_{16}	v_8	v_2	v_{26}	v_{25}	v_2	v_2	v_{32}	v_{25}
(8)	v_{25}	v_{23}	v_{26}	v_{16}	v_{10}	v_5	v_6	v_8	v_{10}	v_6	v_6
(9)	v_2	v_{22}	v_2	v_{29}	v_6	v_8	v_{32}	v_5	v_6	v_{25}	v_{22}
(10)	v_{10}	v_{21}	v_8	v_2	v_{11}	v_{14}	v_{22}	v_{20}	v_{29}	v_{22}	v_{32}

can be further extended by considering suitable properties to identify the important components with respect to function and topology of the nodes and edges (in Figure 6), while, using fuzzy integral fusion ICMs, some nodes (such as v_6) with low values can be also identified as the most important nodes. In addition, the evaluation result of these methods is a larger gap, especially noncritical components. These methods, such as AHP and TOPSIS, are greatly affected by human factors. The accuracy of the most critical components identification results is higher, but other components have great difference on human factors. CMs, which include DC, CC, BC, and EC, identify the critical components of structure.

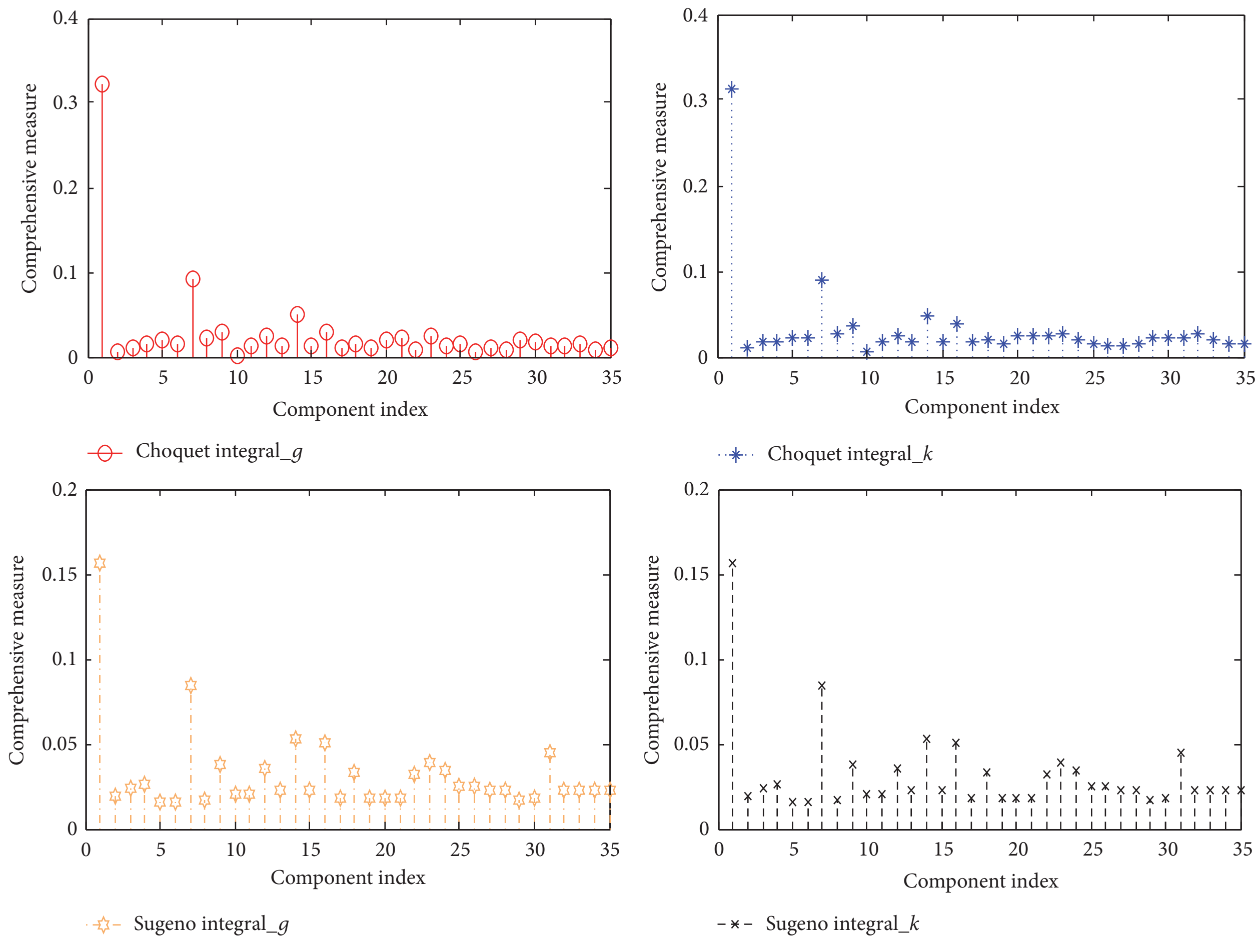

FIGURE 9: Influential components of bogie system.

Therefore, there are some differences in the results of CMs and other measures. In fact, there are still differences of using Sugeno integral and Choquet integral to identify influential components. The most important components are the same, while the ranking of noncritical components is different. This is because the amount of information loss exceeds the threshold value.

With the reduction of the importance of nodes, the difference of all methods in Table 5 for importance of nodes is bigger in Figure 11. For example, the results of the three methods, such as AHP, DC, and EC, are not consistent with practical recognition for node v_7. And, for nodes v_{14}, v_{16}, and v_{31}, the number of methods which are not different from practical recognition, is 4, 7, and 9, respectively. We can see that most methods are effective in identifying the most critical nodes. However, the validity of the identification results of the other nodes is poor.

The methods of integration multimeasures are able to overcome the randomness and uncertainty by using a single measure. Different methods of comprehensive multimeasures are selected, and the accuracy of the identification results is different. Figure 12 presents the accuracy rate of these methods in comparison with practical recognition. The accuracy rate $\mathrm{AR}_i = \mathrm{RN}_i/N$, where RN_i indicates the number of nodes in the ith method which the ranking is consistent with the expert experience, and N_i is the number of nodes in system. We can find that Choquet integral by using k-additive has a higher accuracy rate. The method of integration ICMs with Sugeno integral misses much information in computational procedure. If the amount of information loss exceeds the threshold value, the results will be not accurate.

Through the exploratory discussion above, it is shown that the results acquired from comprehensive measure are, to a certain extent, more reasonable and powerful than those traditional importance measures. Just as mentioned, the system function represents the interactions between components; system topology represents the structure relationship. Therefore, the comprehensive gives consideration to both topological features and physical characteristics of a holistic topological network from multiple perspectives.

6. Conclusions

This paper integrates the literature of mechatronic architecture and complex networks to define holistic topological

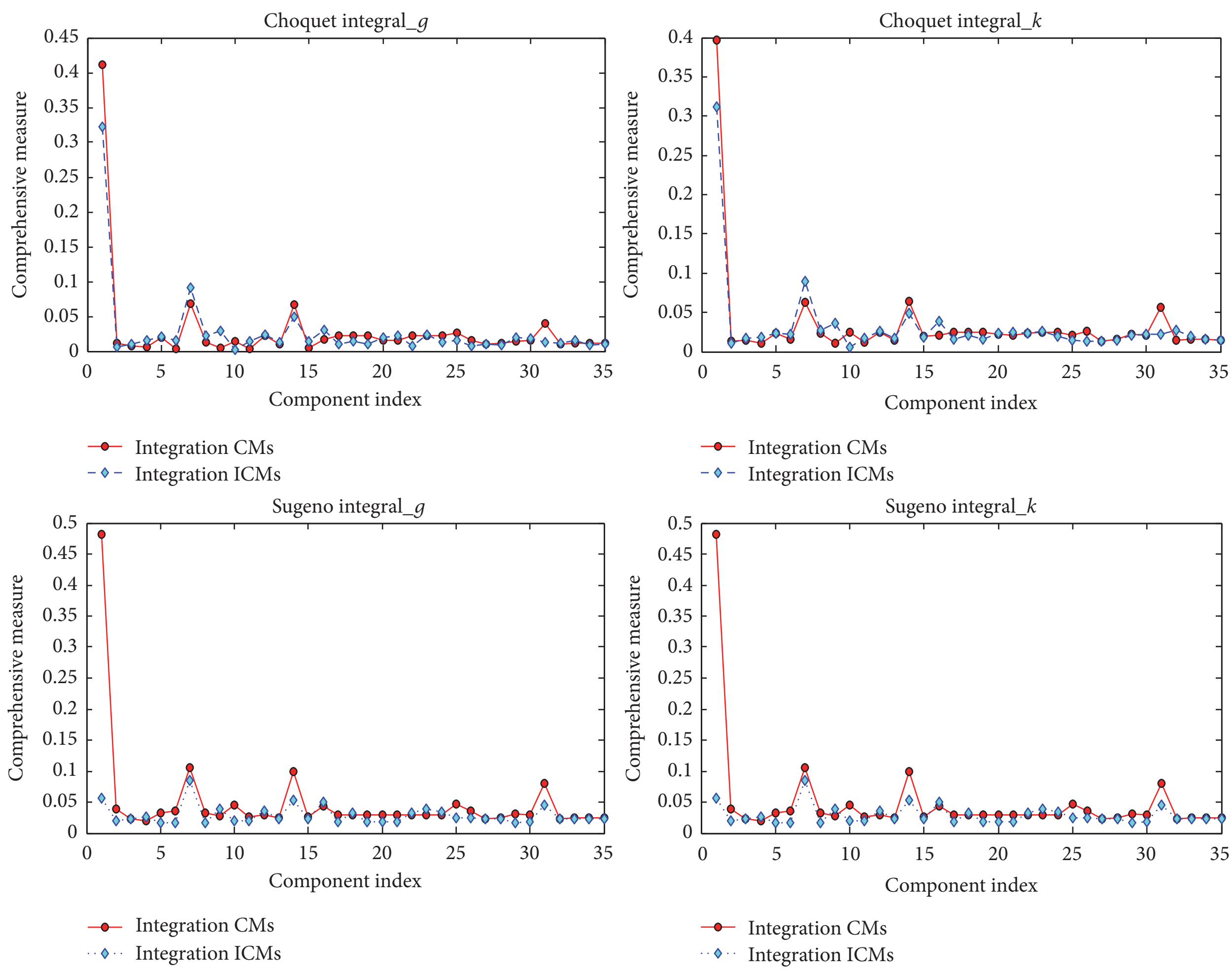

Figure 10: The results of integration CMs and ICMs.

network. And, based on the notion of complex networks, meaningful improved centrality measures (ICMs) are first brought and then comprehensive measure, with first-time, is constructed to identify important components by integrated multi-ICMs. Indeed, construction ICMs with the consideration of functional and topological properties and their relationship is the originality and novelty of proposed measures. Next, integration multi-ICMs based on fuzzy integral, that is, the combination of multiple influencing factors, is also the novelty of comprehensive measure. This paper has also shown the application of the proposed approach in reliability assessment of bogie system of CRHX EMUs. By applying the comprehensive measure, the components importance of bogie system can be evaluated at reasonable human factors. Results indicate that the ranking of critical components can be not the same in selecting different fuzzy integrals. According to the applicable environment, reasonable choices can be determined. In addition, three conclusions are drawn through an exploratory discussion:

(i) The function and topology are of the same importance in electromechanical system. If identifying critical components, these two aspects should be taken into account.

(ii) The method of integration ICMs with Choquet integral by using k-additive has a higher accuracy rate than other methods.

(iii) The result of comprehensive evaluation is better than that of single measure identification.

Of course, due to the diversification and complexity of the real electromechanical system, the model presented here is just a simplification of what happens in actual systems. Several influential factors of critical components in the model need to be further developed if some additional information can be acquired. As previously mentioned, the robustness of comprehensive measure with respect to the fault propagation damping parameter is still under discussion and valuable for further research.

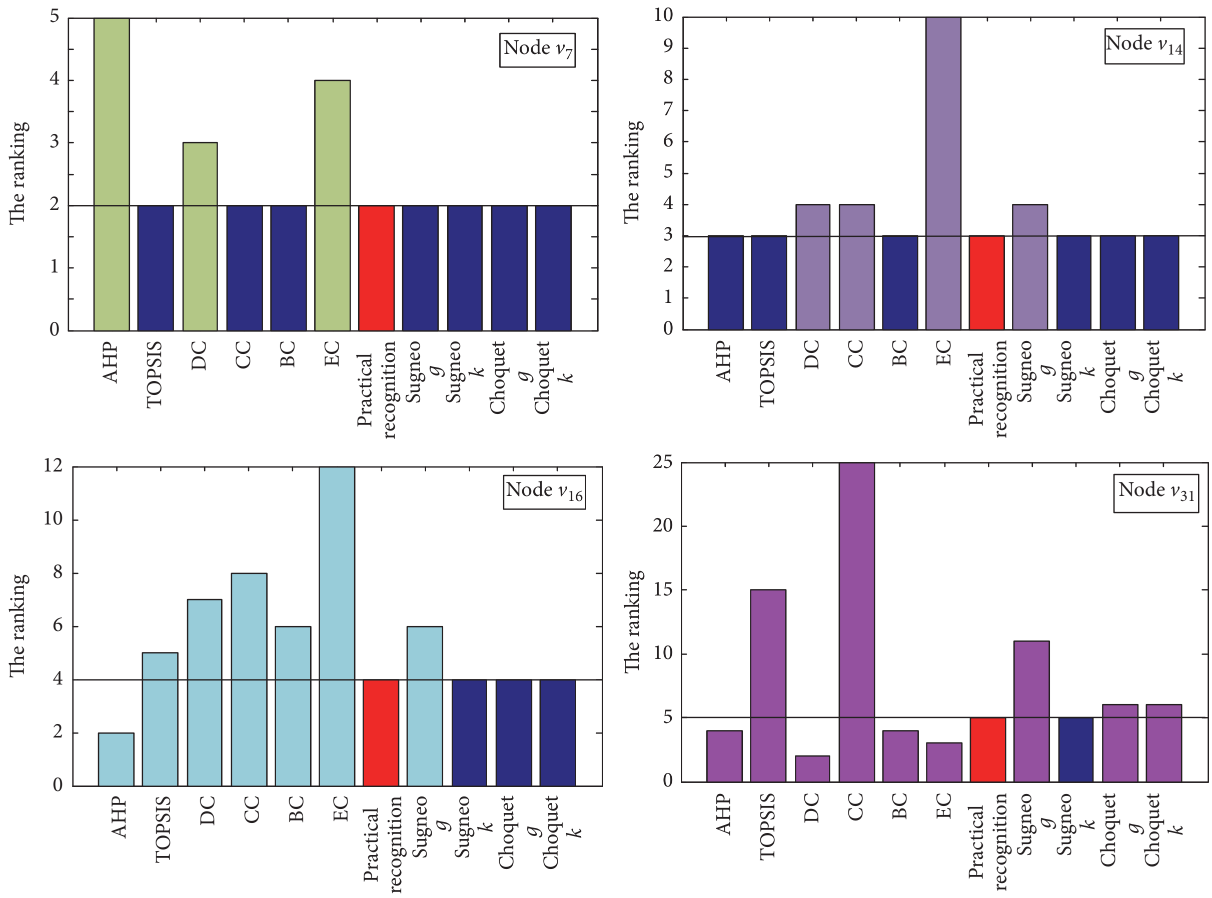

Figure 11: The ranking of partly nodes.

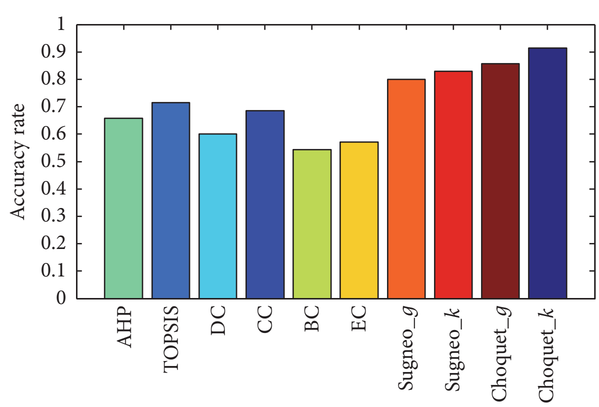

Figure 12: The accuracy rate of these methods.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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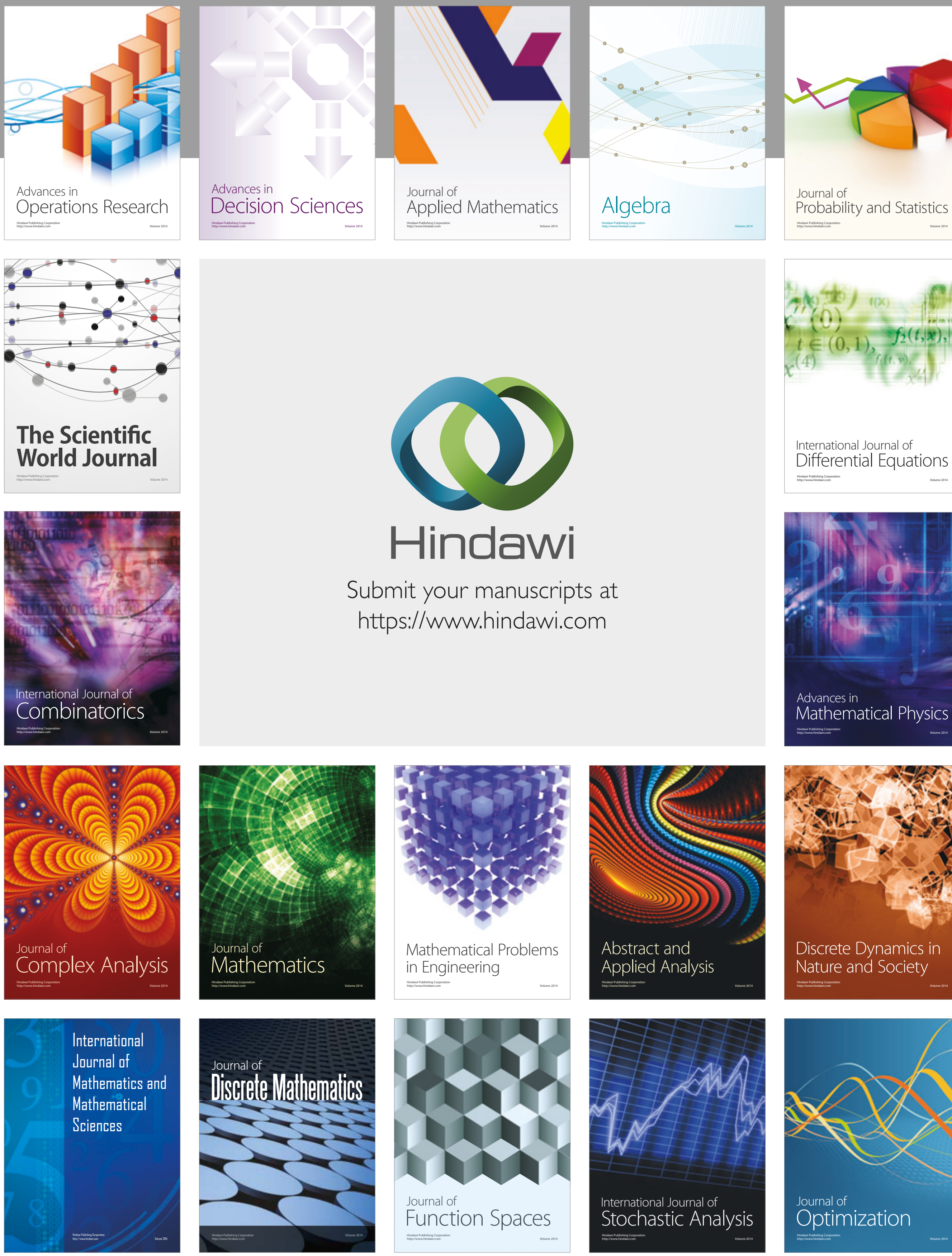
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