DS/ANP Method: A Simplified Group Analytic Network Process With Consensus Reaching

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ABSTRACT Analytic network process (ANP) is a significant multiple criteria decision making (MCDM) method. Although lots of efforts have been spent on improving the ANP, there still exist the four aspects of problems to be solved such as too many comparison times, unconsidering expert knowledge structure, ignoring consensus level of experts’ group and ineffectively determining holistic information of the group. This study focuses on providing a simplified group ANP with consensus reaching named as DS/ANP method which incorporates the Dempster-Shafer theory of evidence (DS) with the ANP. An expert information extraction mechanism with the help of knowledge matrix and basic probability assignment function is introduced to simplify comparisons of group ANP and reflect expert knowledge structure. Then Shafer’s discounting and Dempster’s rule are both used to get the holistic information of the group, in which three levels of consensus indices (element level, cluster level, and holism level) are defined in terms of Jousselme distance. A group ANP method with consensus reaching and its corresponding algorithm are both established by following the principles of ANP. Finally, a numerical example is presented to make comparisons and discussions for the proposed method.

INDEX TERMS Analytic network process, consensus reaching, Dempster’s rule, group decision making, knowledge matrix.

I. INTRODUCTION

The analytic network process (ANP) is a significant tool used in multiple criteria decision making (MCDM) analysis. The ANP was proposed by SAATY in 1996 [1]. As a generalized form of the analytic hierarchy process (AHP) [2], [3] for solving socio-economic decision-making problems involving interdependent relationships within MCDM models. As such, the ANP was developed to address the complexity that can arise in actual decision-making processes [4]. A hierarchical structure with a linear top-to-bottom form is not suitable for complex systems involving such interdependences. The ANP replaces hierarchies with networks in which the relationships between criteria and alternatives are not easily represented as higher and lower, dominant and subordinate, and direct and indirect [5]. The ANP is frequently employed to derive composite-priority-ratio scales from individual-ratio scales [6]. The basic ANP procedure can be summarized as the following three phases: 1) compare the homogeneous elements in a system to form an unweighted supermatrix by pairwise comparisons; 2) derive a weighted supermatrix with columns that sum exactly to 1 by incorporating average weights into the supermatrix; and 3) obtain global priority vectors, or so-called weights, by raising to a sufficiently high power to obtain the limit-weighted supermatrix [7].

The ANP method is a fine technique and has many advantages than other MCDM methods. the characteristics consider the various factors or phases interaction between adjacent levels and using “supermatrix” for the interaction and influence of the factor comprehensive analysis. However, the ANP model does not require strictly hierarchical relationships as in the AHP model. since the ANP has the advantages of being suitable for lots of complex decision problems, it has been employed and widely accepted to deal with a large range of
decision problems. For instance, it has been found in different areas of application which includes evaluating or determining six sigma projects, financial reporting supply chain, turkey’s energy strategy alternatives, and prioritization of ecosystem management [8]–[11].

While the ANP has played a significant role in solving unstructured problems, it suffers from three critical drawbacks when applied to actual decision-making problems. First, the ANP performs poorly at resolving ambiguities in the relationships between elements in the network. While researchers who make comparisons for criteria or alternatives are usually aware of this issue, their different perspectives may result in discrepancies in the information. Efforts to eliminate this ambiguity generally include the application of fuzzy logic methods in the ANP to provide numerical information under conditions of uncertainty, and thereby obtain more realistic results when establishing relationships between elements in the network. Accordingly, the fuzzy ANP-based decision-making approach has been applied to solve complex decision problems such as the evaluation of ship maneuverability, agricultural drought risk evaluation, prioritizing challenges toward implementing the internet of things in countries, and multi-attribute sustainability evaluation of alternative aviation fuels [12]–[15]. Second, the ANP performs poorly at ensuring consistency between preference relations, which is a key aspect for deriving priorities in the decision-making process [16]. As a result, inconsistent preferences can lead to incorrect decisions. Numerous methods have been proposed over the past few decades to evaluate and improve the consistency of preference relations. For example, the concept of the satisfactory consistency index was proposed, along with a method to compute it [17], methods were proposed to improve the ordinal and multiplicative consistencies of preference relations, and reduce the ordinal and additive inconsistencies for reciprocal preference relations [18]–[22], and an additive consistency index was introduced to measure the consistency level of hesitant fuzzy preference relations [23]. Third, obtaining the weighted supermatrix in the ANP by standard normalization, in which each criterion/element in a column is divided by the number of clusters so that the sum of each column is uniformly 1, results in the assessed priorities being higher or lower than they should be under the actual conditions. This issue was addressed in the decision-making trial and evaluation laboratory (DEMATEL) by constructing the interrelations among clusters and deriving the weight of each cluster [24]. This methodology has been successfully applied to various decision-making problems, such as identifying causal relationships in strategy maps, evaluating green suppliers, creating brand values in brand marketing, and improving the partner selection process in customer relationship management [25], [26].

The discussion above indicates that considerable effort has been applied toward improving the ANP from both theoretical and application perspectives, and these achievements have proved to be beneficial for solving many real decision problems more objectively. However, modern decision problems have become increasingly complex with the development of society and the economy. One of the new challenges that has arisen for the ANP is the participation of an increasing number of experts in the decision-making process. This has led to the development of group ANP, which has been extended by fuzzy set theory or rough set theory to make decisions on issues with mutual dependences and feedback from groups of experts. For example, a group extension of the ANP was proposed by adopting the C-OWA operator to aggregate group preferences with interval scales [27], and fuzzy ANP was employed to collect the opinions of experts and prioritize the implementation of low carbon energy systems [28]. Recently, rough group ANP was proposed to assess the opportunity of co-creating value with customers, in which the assessments of experts could be transformed into rough numbers and analyzed in accordance with rough synthetic theory [29], [30].

Note that, experts usually have different knowledge and backgrounds on the decision-making problems, and the non-consensus (conflicting) may be existing in experts’ group. Some group consensus models are established to improve the consensus level either by introducing the methods such as automatic feedback mechanism, twofold feedback mechanism and geometric mean prioritization [31]–[35], or by extending the consensus models into fuzzy environments such as preference relations, hesitant fuzzy preference relations and linguistic preference information [36]–[45]. Unfortunately, the consensus problem has not involved in the field of group ANP.

Despite the substantial progress made in expanding the ANP from different perspectives, a number of problems remain to be solved in the field of group ANP. The first problem involves the exponential growth in the number of pairwise comparison judgments that are required to extract decision information as the number of evaluation criteria/elements increases, which greatly increases the workload of experts, and can lead to erroneous information in the inference process. The remaining problems all hinge upon the fact that experts typically have different levels of knowledge and experience specific to decision-making problems, which affects the decision-making process in different ways. In this regard, the second problem involves the lack of an effective means of addressing the effect of the different levels of knowledge and experience of group members on the quality of decision-making solutions. In the group ANP, all experts are assumed to have equal capabilities for rendering judgments in pairwise comparisons, and therefore give equally effective information. However, the different levels of knowledge and backgrounds of group members indicates that the judgments of some members will be better than those of other members depending on the precise context. As such, an equal weighting for all judgments can be expected to lead to less than optimum decision-making solutions. The third problem involves the lack of a truly effective means of constructing the overall (holistic) information of a group from the individual judgments of its members. Here, no single
expert can be expected to provide accurate assessments of all required judgments in the ANP due to limitations in knowledge and experience. As such, multiple experts are required, and their individual judgments must be combined by some fusion method to obtain the overall information of the group. The fourth problem involves the lack of addressing conditions of non-consensus (conflict) among the judgments of expert group members in the decision-making process. Here, a lack of consensus among experts can be expected to seriously detract from the optimality of decision-making solutions.

The motivation of this paper is to solve the above four aspects of problems by proposing a new method named DS/ANP. The DS/ANP is a hybrid method that combines the Dempster-Shafer theory of evidence (DS) and the ANP, in which the mentioned problems such as too many comparison times, unconsidering expert knowledge structure, ignoring consensus level of experts’ group and ineffectively determining holistic information of group can be well solved. In the proposed method, the first and the second aspects of problems are solved by providing an expert information extraction mechanism with the help of knowledge matrix and basic probability assignment function in the DS and its extensions. The third and the fourth aspects of problems are solved by shafer’s discounting and Dempster’s rule in the DS to get the effective holistic information of the group, in which three levels of consensus indices are defined and a consensus reaching model for group ANP is established. The remainder of this paper is organized as follows. Section II presents a brief review of the basic concepts of ds theory and its extensions as a foundation for later discussion. Section III presents the proposed ds/ANP method. Section IV presents a numerical example for illustrating the decision-making performance of the proposed method, and the main conclusions are summarized in Section V.

II. PRELIMINARIES

In this section, we briefly review some basic concepts of the DS and its extensions. It provides a distributed framework to model probabilistic uncertainties, based on the frame of discernment, basic probability assignment function, knowledge matrix, etc.

Definition 1 [46]: Suppose a possible hypothesis of a variable is \( \theta_n \), where \( n = 1, \cdots, N \), and each of the \( N \) possible hypotheses is exclusive. Then, the frame of discernment is defined as a finite nonempty exhaustive set of all possible hypotheses \( \Theta = \{ \theta_1, \cdots, \theta_N \} \), and its power set that consists of \( 2^\Theta \) subsets of \( \Theta \) is expressed as follows.

\[
P(\Theta) = 2^\Theta = \{ \emptyset, \theta_1, \cdots, \theta_N, \{ \theta_1, \theta_2 \}, \cdots, \{ \theta_1, \theta_2, \cdots, \theta_N \}, \cdots, \Theta \}
\]

(1)

Definition 2 [46]: The BPA function is defined as any mapping function \( m : 2^\Theta \rightarrow [0, 1] \) for \( \Theta = \{ \theta_1, \cdots, \theta_N \} \) that fulfills the following conditions.

\[
\begin{align*}
m(\emptyset) &= 0, & \theta &= \emptyset \\
\sum_{\theta \subseteq \Theta} m(\theta) &= 1, & m(\theta) &> 0, \theta \neq \emptyset
\end{align*}
\]

(2)
\[
\begin{align*}
    b(x_q) &= \frac{a_q}{\sum_{q=1}^{Q} a_q + \sqrt{Q}}, \quad q = 1, \ldots, Q \\
    b(\Theta) &= \frac{\sum_{q=1}^{Q} a_q + \sqrt{Q}}{\sum_{q=1}^{Q} a_q + \sqrt{Q}}
\end{align*}
\]

Definition 8 [51]: Suppose \( m_i \) and \( m_j \) are two BPAs on the same frame of discernment \( \Theta \), containing \( N \) mutually exclusive and exhaustive hypotheses. Then, the Jousselme distance between \( m_i \) and \( m_j \) is defined as follows.

\[
J = \sqrt{\frac{1}{2} (\tilde{m}_i - \tilde{m}_j)^T D (\tilde{m}_i - \tilde{m}_j)}
\]

where \( D \) is a \((2^\Theta \times 2^\Theta)\)-dimensional matrix whose elements are \( D(A, B) = |A \cap B|/|A \cup B| \), and \( A, B \in 2^\Theta \). The Jousselme distance defines a metric distance that represents the similarity among the subsets of \( \Theta \) and is regarded as a standard metric for comparing two sources of evidence (i.e., BPA functions). Given a BPA \( m \) on \( \Theta \), \( \tilde{m} \) is a \( 2^\Theta \)-dimensional column vector (can also be called a \( 2^\Theta \times 1 \) matrix). \( (\tilde{m}_i - \tilde{m}_j) \) stands for vector subtraction and \( \tilde{m}^T \) is the transpose of the vector (or matrix). The Jousselme distance has the ability to measure conflicts or inconsistencies among BPA functions, and is adopted in the present work to measure the degree of expert group consensus.

III. THE PROPOSED METHOD

A. EXPERT INFORMATION EXTRACTION MECHANISM

The ANP is a generalization form of AHP by considering dependence relationships between elements of the hierarchy and is represented by a feedback network [52]. The feedback network structure is composed of cycles connecting the clusters of elements and loops connecting the elements of a cluster to itself. The elements connected by loops are inter-dependent, while all other connections accounting for dependences between clusters are outer-dependent. The impacts of a given series of elements in a cluster on any other elements in the network are reflected by local priority vectors under both inter-dependent and outer-dependent conditions. Similar to the AHP, the local priority vectors can be calculated by pairwise comparisons in which the relative importance of an element is described by a range, such on a scale of 1 to 9, from low importance to extreme importance.

While pairwise comparisons are certainly suitable for extracting judgments in the AHP, it is not entirely clear whether these are suitable for this purpose in the ANP. The first reason is that the required number of pairwise comparisons in the ANP, which must be made not only under outer-dependent conditions, but also under inter-dependent conditions, may be too many to be practicable, as discussed previously. It is logical to find that experts are likely to feel boring which may lead to increase the probability of errors. The second reason is that the quality of pairwise comparisons made in ANP may be not high. Pairwise comparisons are required to be made for each pair of elements by each expert, which is assumed that each expert has the ability to answer all the problems in pairwise comparisons and give effective information. However, if the decision problem exceeds the expert’s cognitive ability, the given decision information may be low qualities resulting in decision results to be debatable.

In order to solve the above two aspects of problems in the traditional ANP, the knowledge matrix introduced in the DS/AHP is employed to extract experts’ judgments in this study. The DS/AHP proposed by Beynon, is a hybrid MCDM method by combining AHP and DS [55]. This approach uses the hierarchical structure of AHP to divide the complex problem into several simple sub-problems and uses the DS to combine the decision information within local and global ignorance. As such, the combination of AHP and DS represents a decision-making process that is more approximate to human intuitional thinking. Within DS/AHP, the set of all decision alternatives is regarded as the frame of discernment and for each criterion, there are certain groups of decision alternatives identified by an expert. Accordingly, the number of groups of alternatives identified by the expert can reflect the level of knowledge possessed by that expert regarding the criterion under consideration. We also note that these groups of alternatives can be employed to construct the knowledge matrix given in (7) with respect to any specific criterion. Therefore, through comparing a group of alternatives to the frame of discernment, the expert will express some degree of favorable knowledge on each of these groups of alternatives. Obviously, it differs from the AHP which makes pairwise comparisons between individual alternatives, this approach compares each identified group of alternatives to all possible alternatives in the frame of discernment.

We introduce the knowledge matrix in the DS/AHP to derive the local priorities in the ANP. Here, the local priorities reflect the degrees of impact that a given element has on other elements in the same cluster or in different clusters. Suppose four clusters are connected, as shown in Figure 1, where \( C \rightarrow C' \) denotes that each element in cluster \( C \) may have an impact on the elements in cluster \( C' \), i.e., \( C = \{c_j|j = 1, \ldots, J\} \) and \( C' = \{c_k|k = 1, \ldots, K\} \). Obviously, the inter-dependent condition exists when \( C \) and \( C' \) are the same (e.g., \( C_1 \rightarrow C_1 \) and \( C_3 \rightarrow C_3 \)). Otherwise, the outer-dependent condition holds (e.g., \( C_1 \rightarrow C_2 \) and \( C_4 \rightarrow C_2 \)). Let each element in \( C \) be a control element and the set of all elements in \( C' \) be impacted elements, such that \( C' \) is regarded as a frame of discernment \( \Theta = C' = \{c_k|k = 1, \ldots, K\} \). Suppose an expert divides the identified elements in \( C' \) into \( L_j \) groups with respect to the control element \( c_j \), i.e., \( g_l^j, l = 1, \ldots, L_j, L_j \leq J \). All elements in \( g_l^j \) have

\[
\text{FIGURE 1. The relationship diagram of clusters.}
\]
the same degrees of favorability, and the set of all groups is denoted by \( G_j = \{ g'_l | l = 1, \cdots, L_j, L_j \leq J \} \). The expert is also asked to compare \( g'_j \) with \( \Theta \) and assign a corresponding degree of favorability \( d_{ij} \), \( i = 1, \cdots, L_j \), on a scale of 2 to 6, where 2 represents moderate importance and 6 represents high importance, as shown in Table 1. Accordingly, the values of \( d_{11}, \cdots, d_{L_j} \) are employed to obtain the knowledge matrix \( A_j \) with respect to \( c_j \) as shown in (10).

\[
A_j = \begin{pmatrix}
1 & 0 & \cdots & 0 & d_{11} \\
0 & 1 & \cdots & 0 & d_{21} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & \cdots & \cdots & 0 & d_{L_j 1} \\
0 & 1 & \cdots & 1 & d_{L_j L_j}
\end{pmatrix}
\]  

(10)

Then, the local priority vector \( b_j \) corresponding to \( A_j \) can be calculated according to (8) and shown in (11).

\[
b_j = \begin{cases}
\frac{d_{ij}}{\sum_{l=1}^{L_j} d_{ij} + \sqrt{L_j}} & \text{for } i = 1, \cdots, L_j \\
\frac{b_j(\Theta)}{\sum_{l=1}^{L_j} d_{ij} + \sqrt{L_j}} & \text{else}
\end{cases}
\]  

(11)

The local priority vector given in (11) for control element \( c_j \) is the BD given by the expert, and can also be denoted as \( b_j = \{ (g'_l, b_j(g'_l)) | l = 1, \cdots, L_j; (\Theta, b_j(\Theta)); \sum_{l=1}^{L_j} b_j(g'_l) = b_j(\Theta) = 1 \}, j = 1, \cdots, J \). The element groups given by one expert may be different with respect to two different control elements in \( C \), i.e., the element groups \( \{ g'_1, \cdots, g'_{L_j} \} \) given by the expert with respect to \( c_j \) may not be equal to the element groups \( \{ g'_1, \cdots, g'_{L_j} \} \) with respect to \( c_{j'}, j \neq j' \). The BDs for the different control elements can be given with unique forms by denoting the power set of elements in impacted cluster \( C' = \{ c_k | k = 1, \cdots, K \} \) as in (12). The BD \( b_j \) can be transformed into distribution \( d_j \) on power set \( P(C') \) as in (13). The transformation from \( b_j \) to \( d_j \) is determined by following principles: if \( h_l \in \{ g'_1, \cdots, g'_{L_j} \}, (d_j(h_l)) = b_j(g'_l) \) where \( h_l = g'_l \); else \( h_l \not\in \{ g'_1, \cdots, g'_{L_j} \}, (d_j(h_l)) = 0 \).

\[
P(C') = (h_1, \cdots, h_{2^K - 1})
\]

\[
= (c_1, \cdots, c_K, \{ c_1, c_1 \}, \cdots, \{ c_1, \cdots, c_K \}, \cdots, \{ c_1, \cdots, c_K \})
\]  

(12)

\[
d_j = (d_j(h_1), \cdots, (h_{2^K - 1}, d_j(h_{2^K - 1})); \sum_{i=1}^{2^K - 1} d_j(h_i) = 1), j = 1, \cdots, J
\]  

(13)

Note that, the BDs on all control elements in \( C \) could be made up of a matrix as shown in (14). The constructed matrix \( D \) is similar to the block matrix in the traditional ANP, but the former is distributed on the power set \( P(C') \) while the latter is distributed on \( C' \). Besides, the constructed matrix \( D \) is degenerated into the block matrix in the traditional ANP when the expert is capable of making judgments on each element of \( C' \) (\( G_j = \{ g'_1, \cdots, g'_{L_j} \} = \{ c_1, \cdots, c_K \} \)). Obviously, following the above information extraction mechanism, we can obtain the local priority vector corresponding to each pair of connected clusters in the network of ANP whether for the inter-dependent or for the outer-dependent case.

\[
D = [d'_1, \cdots, d'_J]
\]  

\[
= \begin{pmatrix}
d_1(h_1) & d_2(h_1) & \cdots & d_J(h_1) \\
d_1(h_2) & d_2(h_2) & \cdots & d_J(h_2) \\
\vdots & \vdots & \ddots & \vdots \\
d_1(h_{2^K - 1}) & d_2(h_{2^K - 1}) & \cdots & d_J(h_{2^K - 1})
\end{pmatrix}
\]  

(14)

In the above information extraction mechanism, the knowledge structure of each expert could be well reflected by knowledge matrix. The greatest contribution of the knowledge matrix is to effectively formulate a theoretical information reduction framework for complex contexts and reasonably develop a reduction procedure for extracting decision information. Each expert only needs to make judgments on the elements that coincided with his/her recognition ability, while he/she is allowed to give nothing for those elements that exceed his/her recognition ability. This decreases the number of comparisons required in the ANP, and also increases the quality of the comparisons. As such, it is obvious to find that the above two aspects of problems in the traditional ANP could be well solved.

**B. CONSENSUS INDICES IN GROUP ANP**

The block matrix given by (14) contains the judgments assigned by a single expert for a pair of connected clusters \( C \rightarrow C' \). However, group ANP generally consists of \( I \) experts, where each expert may assign a block matrix. Suppose the block matrix given by \( e_i \) with respect to connected clusters \( C \rightarrow C' \) is \( D_i = [d'_{i1}, \cdots, d'_{iJ}] \), where \( d_{ij} = (h_1, d_i(h_1)), \cdots, (h_{2^K - 1}, d_i(h_{2^K - 1})); \sum_{i=1}^{2^K - 1} d_i(h_i) = 1), j = 1, \cdots, J, i = 1, \cdots, I \). According to past discussion, the block matrices given by any two experts may be different (\( D_i \neq D_{i'} \) for \( i \neq i' \)) owing to their different levels of knowledge and experience. As such, differences between the block matrices given by any two experts can be employed to determine the level of importance that should be attached to the judgments of each expert when combining the judgments of the entire group. Moreover, differences in the information contained within the block matrices given by experts can be employed to gauge their level of consensus on their problem evaluations, which can then be employed to engage experts.

| Knowledgeable Scale Knowledgeable Scale |
|----------------------------------------|
| Extremely importance 6 Moderately to strongly 3 |
| Strongly to extremely 5 Moderately importance 2 |
| Strongly importance 4 --- --- |

**TABLE 1.** The 2-6 scales in pairwise clusters.

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in an exchange of information toward obtaining greater consensus. How to take the importance degrees of experts into account and calculate the consensus level of experts’ group for their given block matrices is a key problem.

Without loss of generality, suppose the weight of expert \( e_i \), which is used to define that expert’s degree of importance, is denoted as \( w_i, 0 \leq w_i \leq 1, i = 1, \cdots, I \), where \( w_i = 0 \) indicates that expert \( e_i \) has no importance, while \( w_i = 1 \) indicates that the expert has the maximum importance, such that \( \sum w_i \) is usually equal to 1, but not necessary. The weights of experts can be determined by subjective methods, objective methods, or hybrid methods. If we regard expert \( e_i \) as the \( i^{th} \) evidence source, the block matrix \( D_i = \{ d_{ij}, \cdots, d_{ij} \} \) can be seen as a body of evidence generated by \( e_i \). Accordingly, it is not difficult to find that the block matrix is capable of being discounted by the weight \( w_i \). This is conducted by introducing \( d_{ij} \) and \( w_i \) into (5), and generating the following BPA function for expert \( e_i \) as shown in (15). Obviously, the block matrix discounted by expert weight can be denoted by \( M = \{ m'_{ij}, \cdots, m'_{ij} \}, i = 1, \cdots, I \).

\[
m_{ij} \equiv m_{ij}(h_i) = \begin{cases} w_i d_{ij}(h_i), & l = 1, \cdots, 2^K - 2 \\ w_i d_{ij}(h_i) + (1 - w_i) d_{ij}(h_i), & l = 2^K - 1 \end{cases}
\]

The block matrix discounted by expert weight is denoted by \( M = \{ m'_{ij}, \cdots, m'_{ij} \}, i = 1, \cdots, I \), which is constructed from J segments of BPA functions given by expert \( e_i \) for a pair of connected clusters \( C \rightarrow C' \). Then, we employ Dempster’s rule given in (3) to combine the discounted block matrices given by all experts for \( C \rightarrow C' \) to obtain a collective block matrix \( M = \{ m'_{ij}, \cdots, m'_{ij} \} \), where \( \oplus \) is the orthogonal sum operator and \( m'_{ij} \) can be determined as follows.

\[
m'_{ij} = m'_{ij} \oplus \cdots \oplus m'_{ij}(\varnothing) = \sum_{h_i \cap \cdots \cap h_i = 0} \prod_{1 \leq l < L} m_{lj}(h_l) = 1 - \sum_{h_i \cap \cdots \cap h_i = 0} \prod_{1 \leq l < L} m_{lj}(h_l) \quad (16)
\]

The most common method for calculating consensus index is usually based on similarity or distance between the individual and the collective. Here the individual opinions are the discounted block matrix of each expert \( M = \{ m'_{ij}, \cdots, m'_{ij} \} \) and the collective opinions are the collective block matrix of the group \( M = \{ m'_{ij}, \cdots, m'_{ij} \} \). In the literature, several methods have been introduced to calculate the distance and each distance computing method has its advantages and disadvantages. Jousselme put forward a distance as shown in (9), which is regarded as a standard metric for two pieces of evidence (BPA functions). Jousselme distance has the ability to measure conflicts or inconsistencies among BPA functions, and thus we adopt it to measure the group consensus index in this study. Because the distance is inversely proportional to similarity, i.e., the smaller the distance, the bigger the similarity, we define the degree of similarity between the individual and the collective as follows.

\[
s_{ij} = 1 - J(m'_{ij}, m'_{ij}) = 1 - \sqrt{\frac{1}{2} (m'_{ij} - m'_{ij})^T D(m'_{ij} - m'_{ij})} \quad (17)
\]

According to the framework of consensus reaching model, the consensus index which are used to describe the inconsistency or conflict among experts can be classified into three hierarchical levels such as attribute (low) level, alternative (middle) level and expert (high) level. Similarly, here we also define the consensus index in group ANP with three levels, i.e., element level, cluster level, and holism level. For convenience, we denote the degree of similarity between the expert \( e_i \) and the group on a control element \( c_k \) in \( C_j \) for a pair of connected clusters \( C_j \rightarrow C'_j \) by \( s_{ij} \), \( i = 1, \cdots, I; j, j' = 1, \cdots, J; k_j = 1, \cdots, K_j \). The three levels of consensus indices in group ANP can be defined and their relationship is shown in Figure 2.

**FIGURE 2.** The relationship of three consensus levels for each expert.

**Level 1.** Consensus index at the element level. The consensus index of expert \( e_i \) with respect to the group based on control element \( c_j \) for connected clusters \( C_j \rightarrow C'_j \) is given as follows.

\[
C_{ij}^{k_j} = s_{ij}^{k_j} \quad (18)
\]

**Level 2.** Consensus index at the cluster level. The consensus index of expert \( e_i \) with respect to the group for connected clusters \( C_j \rightarrow C'_j \) is given as follows.

\[
C_{ij} = \frac{1}{K_j} \sum_{k_j=1}^{K_j} C_{ij}^{k_j} \quad (19)
\]

**Level 3.** Consensus index at the holistic level. The consensus index of expert \( e_i \) with respect to the group for all connected clusters is given as follows.

\[
C_i = \frac{1}{J} \sum_{j=1}^{J} \sum_{j'=1}^{J} C_{ij} \quad (20)
\]

We note that the consensus index between expert \( e_i \) and the group increases with increasing \( C_i \), and a value of \( C_i = 1 \)
indicates that expert $e_i$ has a block matrix that is equivalent to the group collective block matrix, which represents unanimous agreement.

**C. CONSENSUS REACHING MODEL IN GROUP ANP**

In group ANP, it is preferable that a group of experts reach a high level of consensus index amongst their opinions. However, the experts in the group usually come from multiple organizations with different knowledge structures. It may arise conflicts in the decision making and lead to inconsistency problems among the group. It is obvious to find that expert $e_i$ has the same block matrix with that of the group when $CI_i = 1$. However, this situation is rare in practice. As a result, a consensus threshold value $\gamma$ such as 0.9, 0.8, two-thirds is set as a minimum level to achieve. The present work proposes a consensus reaching model for group ANP based on the defined consensus indices, and establish a feedback mechanism that is implemented according to a consensus threshold value $\gamma$ representing a minimum allowable group consensus. In the consensus reaching model, a dynamic and iterative process is introduced to exchange information and tries to persuade a part of experts to alter their opinions. If there exists $CI_i > \gamma$, then an interaction procedure is activated to help inconsistent experts to improve their knowledge matrices with the aim of increasing the consensus indices with respect to the group. Otherwise, an appropriate decision-making process is applied to derive the solutions based on consensus opinions. Mathematically, the steps for identifying those opinions to be further modified are as follows.

**Step 1.**Experts with a consensus index at the holistic level $CI_i$ less than the threshold value $\gamma$ are identified as follows.

$$ECI = \{i | CI_i < \gamma\} \quad (21)$$

**Step 2.**For the identified experts in Step 1, their block matrices with a consensus index $CI_{ij \rightarrow j'}$ less than the threshold $\gamma$ are identified as follows.

$$BCI = \{(i, j \rightarrow j') | i \in ECI \land CI_{ij \rightarrow j'} < \gamma\} \quad (22)$$

**Step 3.**All control elements within knowledge matrices requiring modification are identified as those with a consensus index at the element level $CI_{ij \rightarrow j'}$ less than the threshold $\gamma$ as follows.

$$KCI = \{(i, j \rightarrow j', k_j) | (i, j \rightarrow j') \in BCI \land CI_{ij \rightarrow j'} < \gamma\} \quad (23)$$

The recommendation produces personalized advice for those experts on how to modify their knowledge matrices to increase their consensus level. Given $(i, j, k_j) \in KCI$, expert $e_i$ receives the following personalized advice rules as:

“You are suggested to change the knowledge matrix $A^{k_j}_{(i)j \rightarrow j'}$ for control element $c_{k_j}$ in the connected clusters $C_j \rightarrow C_j'$, and make its BPA function more close to collective opinion $m_{ij \rightarrow j'}$."

Once all the experts have been modified their knowledge matrix $A^{k_j}_{(i)j \rightarrow j'}$ for $(i, j, k_j) \in KCI$, block matrix $D_i = [d_{ij1}, \ldots, d_{ijm}]$ which is constructed by BDs and that discounted by expert weights $M_i = [m_{ij1}, \ldots, m_{ijm}]$ are both capable of being calculated by (11)-(15), $i = 1, \ldots, I$. After that, the consensus indices of group ANP at three levels are also capable of being calculated by (21)-(23). If $CI_i \leq \gamma$ for $i = 1, \ldots, I$, it means that the opinions of all experts have been reached enough consensus level, based on which the final decision can be made by following the process of group ANP. Otherwise, a new-round interaction procedure is activated to help inconsistent experts improving their knowledge matrices and increasing the consensus level.

Suppose the knowledge matrix given by expert $e_i$ at the $t^{th}$ time is denoted by $A^{k_j}_{(i)j \rightarrow j'}$, its corresponding BD is denoted by $d_{(i)j \rightarrow j'}$, $i = 1, \ldots, I$; $j, j' = 1, \ldots, J$; $k_j = 1, \ldots, K_j$. At the $t^{th}$ time, the block matrix constructed by BDs and that discounted by expert weights are respectively denoted by $D_{(i)j \rightarrow j'} = [d^{k_j}_{(i)j \rightarrow j'}, \ldots, d_{(i)j \rightarrow j'}^{K_j}]$ and $M_{(i)j \rightarrow j'} = [m^{k_j}_{(i)j \rightarrow j'}, \ldots, m_{(i)j \rightarrow j'}^{K_j}]$; the consensus indices at three levels are denoted by $CI_{(i)j \rightarrow j'}$, $BCI_{(i)j \rightarrow j'}$ and $KCI_{(i)j \rightarrow j'}$, the sets of identified ones at three levels as in (21)-(23) are denoted by $ECI_{(i)j \rightarrow j'}$, $BCI_{(i)j \rightarrow j'}$, $KCI_{(i)j \rightarrow j'}$. It is obvious to find that the interaction is ended once $CI_{(i)j} \leq \gamma$ or less than the threshold value $\gamma$ for all experts. The above adjustment process can be shown as in Figure 3. It is easy to find that the above adjustment process is very similar to the process adopted by the Delphi method.

**D. GROUP ANP WITH CONSENSUS REACHING**

Suppose the finally adjusted block matrix given by expert $e_i$ on element $c_{j'}$ for control element $c_j$ is $M_{(i)j \rightarrow j'} = [m^{k_j}_{(i)j \rightarrow j'}, \ldots, m^{k_j}_{(i)j \rightarrow j'}]$, $i = 1, \ldots, I$, $j, j' = 1, \ldots, J$, which is employed as an integral part of the input of group ANP to make a final decision. As discussed, Dempster’s rule is then employed to combine the final block matrices and derive $M_{(T)j \rightarrow j'} = [m^{k_j}_{(T)j \rightarrow j'}, \ldots, m^{k_j}_{(T)j \rightarrow j'}]$, where $m^{k_j}_{(T)j \rightarrow j'} = m^{k_j}_{(1)j \rightarrow j'} \oplus \ldots \oplus m^{k_j}_{(m)j \rightarrow j'}$, $i = 1, \ldots, I$, $j, j' = 1, \ldots, J$. Actually, block matrix $M_{(n)j \rightarrow j'}$ for $j, j' = 1, \ldots, J$ has been determined at the last time of adjustments when calculating three levels of consensus indices. According to the structure of the supermatrix in ANP, we similarly construct the matrix as in (24) on the basis of the
combined block matrices.

The constructed matrix as in (24) is different from the supermatrix defined in the traditional ANP method. The supermatrix of traditional ANP is a square matrix and each column of that is distributed on singleton elements of clusters, while the matrix in (24) is not a square matrix and each column of that is distributed on the power set of elements in clusters. However, all implementations of the ANP rely on a supermatrix. Therefore, the matrix in (24) must be transformed into a supermatrix suitable for use in the ANP. Accordingly, we refer herein to the matrix in (24) as a precursor supermatrix, and investigate the important problem of its transformation in the following discussion.

Because each column of a block matrix in the precursor supermatrix is a BPA function in which there may exist uncertain probabilities such as local ignorance or global ignorance, it is necessary to reassign uncertain probabilities as certain probabilities for each single element. The pignistic probability function defined as in (6) is the most popular transformation method which can well integrate the belief function with the plausibility function, thus we employ it to make such a transformation. Supposing a frame of discernment \( \Theta_f = C_f = \{c_{k_f}\} f = 1, \ldots, K_f \), we apply \( m_{(T)}^{k_f} \) in (6) and calculate the pignistic probability of element \( c_{k_f} \) in the impacted cluster \( C_f \) as follows.

\[
P_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) = Bel_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) + \varepsilon_{(T)j\rightarrow j'}^{k_f} \cdot P_{(T)j\rightarrow j'}^{k_f}(c_{k_f})
\]

where

\[
Bel_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) = \sum_{c_{k_f} \subseteq \theta} m_{(T)j\rightarrow j'}^{k_f}(\theta), P_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) = \sum_{c_{k_f} \not\subseteq \theta} m_{(T)j\rightarrow j'}^{k_f}(\theta), \varepsilon_{(T)j\rightarrow j'}^{k_f} = 1 - \sum_{c_{k_f} \subseteq \theta} Bel_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) / \sum_{c_{k_f} \subseteq \theta} P_{(T)j\rightarrow j'}^{k_f}(c_{k_f}), j, j' = 1, \ldots, J, k_f = 1, \ldots, K_f.
\]

From (24), we note that the pignistic probability \( P_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) \) transformed from \( m_{(T)j\rightarrow j'}^{k_f} \) is a probability distribution based on single elements rather than on the power set of elements. Then, we obtain the block matrix constructed by pignistic probabilities \( P_{(T)j\rightarrow j'}^{k_f} = [p_{(T)j\rightarrow j'}^{k_f}, \ldots, p_{(T)j\rightarrow j'}^{k_f}] \) with respect to the control cluster \( C_f \), and replace \( M_{(T)j\rightarrow j'}^{k_f} \) with \( P_{(T)j\rightarrow j'}^{k_f} \) in (24) to obtain the following square supermatrix as shown in (26).

\[
P_{(T)j\rightarrow j'}^{k_f}(c_{k_f}) = \begin{pmatrix} c_{11} \ldots c_{1K_1} & \cdots & c_{j1} \ldots c_{JK_j} \\ \vdots & \ddots & \vdots \\ c_{j1} \ldots c_{JK_j} & \cdots & \begin{pmatrix} P_{k_f}(T)j\rightarrow j' & \cdots & P_{k_f}(T)j\rightarrow j' \\ \vdots & \ddots & \vdots \\ \cdots & \cdots & P_{k_f}(T)j\rightarrow j' \\
\end{pmatrix} \\ \end{pmatrix}
\]

In group ANP, the weighted supermatrix should be calculated such that the sum of the elements in each column is 1 (i.e., the columns are normalized). The present work addresses problems associated with the normalization process of ANP by applying the normalization approach developed in the DEMATEL, which determines the weights of clusters in terms of interrelations among the clusters. The weight determination process is not the focus of this study, so we assume that the determined weight of the block matrix \( P_{(T)j\rightarrow j'} = \lambda_{(T)j\rightarrow j'}, j, j' = 1, \ldots, J \) whether this is determined by the conventional method or by the method adopted in the DEMATEL. As a result, the weight matrix is constructed as \( \lambda = (\lambda_{(T)j\rightarrow j'})_{J \times J} \). Accordingly, we obtain the weighted supermatrix \( S_2 \) by multiplying the weight matrix \( \lambda \) with the supermatrix \( S_1 \), which is given as (27), shown at the bottom of the next page.

Finally, we determine the limit-weighted supermatrix \( S_3 = \lim_{x \rightarrow +\infty} (S_2)^x \) by raising it to a sufficiently large power so that it converges into a stable supermatrix. It has been proved that the results in a long-term stable matrix that tends toward uniformity when \( x \) approaches infinity. Then, the final priority of each element in the clusters can be obtained according to \( S_3 \), and the so-obtained priorities of alternatives can be used to make the decision.

The simplified group ANP with consensus reaching is summarized as Algorithm 1. Algorithm 1 includes a relationship matrix of clusters \( R = \{r_{jf}\}_{J \times J} \), which is transformed from the relationship diagram of the clusters according to the following process: if \( C_j \rightarrow C_f \), set \( r_{jf} = 1 \); else, set \( r_{jf} = 0 \), \( j, j' = 1, \ldots, J \).

IV. NUMERICAL COMPARISON AND DISCUSSION

Marine resources weigh heavily in the economic and social development of nations. However, the shortage of land resources, rapid population growth, severe ecological damage, and environmental deterioration yield numerous problems when seeking to develop marine resources. Therefore, conflicts between the development of marine resources,
ecology, and environment have become an increasingly important constraint for the sustainable development of the marine economy in China. As such, sustainable marine economy development requires an in-depth analysis of the carrying capacity of the marine ecology in different areas.

Suppose three experts in the field of marine management are invited to evaluate the marine ecological carrying capacity for three regions (alternatives) with an evaluation system as following aspects [53]. As discussed by experts, the structure of problem is described by a network consisting of five related clusters as in Figure 4 [54], [55].

1. Marine resource supply (A): production of marine aquatic product (c₁), production of marine salt (c₂), production of marine crude oil (c₃), and production of marine natural gas (c₄).

2. Marine economic development (B): proportion of marine tertiary industry to gross domestic product (c₅), GDP of regional marine assets (c₆), and total output value of marine industries (c₇).

3. Scientific and technological support conditions (F): number of marine scientific research institutions (c₈), number of graduates in marine specialties (c₉), and quantity of scientific papers on marine resource (c₁₀).

4. Marine social pressure (D): number of people in coastal areas (c₁₁), turnover of coastal goods (c₁₂), turnover of coastal passenger flows (c₁₃), and discharge of pollutants from direct discharge to sea (c₁₄).

5. Marine ecological carrying capacity of three different regions (Y): region 1 (c₁₅), region 2 (c₁₆), and region 3 (c₁₇).

**A. APPLICATION OF THE PROPOSED METHOD**

According to the proposed method in section III, we derive the details as below to evaluate the marine ecological carrying capacity. Suppose three experts e₁, e₂ and e₃ are asked to make judgments on five aspects A, B, F, D and Y. Three experts are assigned importance weights of 0.5, 0.3 and 0.2, respectively, and a consensus threshold of γ = 0.7 is uniformly applied at the element level, cluster level, and the holistic level. The specific steps of the decision process are given as follows.

**Step 1:** Decompose the problem and construct the network for the marine ecological carrying capacity of three regions. The network of clusters is the same as in Figure 4. And the relationship of clusters is listed in Table 2, where 1 represents the influence exists between connected clusters, and 0 represents the influence does not exist between them.

**Step 2:** Extract the judgment information of experts and construct knowledge matrices. The system includes five clusters {A, B, F, D, Y} and each cluster includes several elements, i.e., A = {c₁, c₂, c₃, c₄}, B = {c₅, c₆, c₇}, F = {c₈, c₉, c₁₀}, D = {c₁₁, c₁₂, c₁₃, c₁₄}, Y = {c₁₅, c₁₆, c₁₇}. According to the step 1 of Algorithm 1, the knowledge

$$
S_2 = \begin{pmatrix}
C_1 & \cdots & C_J \\
\begin{pmatrix}
c_{11} \\ c_{1K_1} \\
\vdots \\
c_{1K_1} \\
\end{pmatrix} & \cdots & \begin{pmatrix}
c_{J1} \\ c_{JK_J} \\
\vdots \\
c_{JK_J} \\
\end{pmatrix} \\
\end{pmatrix}
\begin{pmatrix}
w_{T;1\rightarrow1}P_{T;1\rightarrow1} & \cdots & w_{T;1\rightarrow1}P_{T;1\rightarrow1} \\
\vdots & \ddots & \vdots \\
w_{T;J\rightarrow1}P_{T;J\rightarrow1} & \cdots & w_{T;J\rightarrow1}P_{T;J\rightarrow1} \\
\end{pmatrix}
$$

(27)
Algorithm 1 Simplified Group ANP Algorithm With Consensus Reaching

**Input:** Expert set $E = \{e_i | i = 1, \cdots, I\}$; Cluster set $C = \{C_j | j = 1, \cdots, J\}$, where $C_j = \{c_{kj} | k_j = 1, \cdots, K_j\}$; Weight set of experts $W = \{w_i | w_i \geq 0, i = 1, \cdots, I\}$; Relationship matrix of clusters $R = [r_{ij}]_{I \times J}$; Consensus threshold $\gamma$.

**Output:** Priorities of elements in $C$.

1. \[ t = 1, KCI_t = \{(i, j \to j', k_j) | \forall i, \forall j, j', \forall k_j\} \]

**Step 1: Construct the knowledge matrices**

For $j = 1 : J$

For $j' = 1 : J$

For $k_j = 1 : K_j$

If $(i, j \to j', k_j) \in KCI_t$ Then

Give/modify knowledge matrix $A_{i(j)j'j'}^{k_j}$ by expert $e_i$

Else $A_{i(j)j'j'}^{k_j} = A_{i(j-1)j'j'}^{k_j}$

EndIf

EndFor

For $i = 1 : I$

Compute the BD of $A_{i(j)j'j'}^{k_j}$ by (11) and derive $d_{i(j)j'j'}^{k_j}$

Discard $d_{i(j)j'j'}^{k_j}$ with $w_i$ by (15) and derive $m_{i(j)j'j'}^{k_j}$

EndFor

Make combination on $C_j \to C_j$ by (16) and derive $m_{i(j)j'j'}^{k_j}$

For $i = 1 : I$

Compute similarity degree by (17) and derive $s_{i(j)j'j'}^{k_j}$

Compute consensus index at element levels by (18) and derive $C_{i(j)j'j'}^{k_j}$

EndFor

For $i = 1 : I$

Compute consensus index at cluster levels by (19) and derive $C_{i(j)j'j'} = \sum_{k_j=1}^{K_j} C_{i(j)j'j'}^{k_j} / K_j$

EndIf

EndFor

For $i = 1 : I$

Compute consensus index at holism levels by (20) and derive $C_{i(j)} = \sum_{j=1}^{J} \sum_{j'=1}^{J} C_{i(j)j'j'} / J^2$

EndFor

**Step 2: Consensus reaching model in group ANP**

Derive invalid expert set by (21) and derive $ECI_t = \{(i, j) | C_{i(j)} < \gamma\}$

Derive invalid block matrix set by (22) and derive $BCI_t = \{(i, j \to j') | i \in ECI_t \land C_{i(j)j'j'} < \gamma\}$

**Algorithm 1 (Continued):** Simplified Group ANP Algorithm With Consensus Reaching

Derive invalid knowledge matrix set by (23) and derive $KCI_t = \{(i, j \to j', k_j) | (i, j) \in BCI_t \land C_{i(j)j'j'}^{k_j} < \gamma\}$

If $KCI_t \neq \emptyset$ Then

For each $(i, j \to j', k_j) \in KCI_t$

Display for expert $e_i$ with “You should change your knowledge matrix $A_{i(j)j'j'}^{k_j}$ and make its BPA function more close to a collective opinion $m_{i(j)j'j'}^{k_j}$”.

EndFor

$t = t + 1$

Return to Step 1

Else Turn into Step 3

EndIf

**Step 3: Group ANP method with consensus reaching**

Let $T = t$

For $j = 1 : J$

For $j' = 1 : J$

Construct the final block matrix $M_{(T)j'j'} = [m_{(T)j'j'}^{1}, \cdots, m_{(T)j'j'}^{K_j}]$

For $k_j = 1 : K_j$

Compute pignistic probability by (25) and derive $P_{(T)j'j'}^{k_j}$

EndFor

Construct block matrix $P_{(T)j'j'} = [P_{(T)j'j'}^{k_1}, \cdots, P_{(T)j'j'}^{k_{K_j}}]$

EndFor

Construct supermatrix $S_1 = [P_{(T)j'j'}]_{I \times J}$

Determine the weights of block matrices $\lambda = (\lambda_{(T)j'j'})_{I \times J}$

Determine the weighted supermatrix $S_2 = [\lambda_{(T)j'j'} \cdot P_{(T)j'j'}]_{I \times J}$

Determine limit weighted supermatrix $S_3 = \lim_{T \to +\infty}(S_2)^T$

Output the priorities of elements from $S_3$

End

**Table 3. Knowledge matrix given by expert $e_1$.**

| $h_l^1$ | $h_l^2$ | $\theta$ |
|-------|-------|-------|
| 1     | 0     | 4     |
| 0     | 1     | 2     |
| $\frac{1}{2}$ | $\frac{1}{2}$ | 1 |
TABLE 4. Consensus index values at element level.

| expert cluster | \( A \) | \( B \) | \( F \) | \( D \) | \( Y \) |
|----------------|-------|-------|-------|-------|-------|
| \( e_1 \) | 0.9443 | 0.9093 | 0.8967 | 0.9117 | 0.0000 |
| \( e_2 \) | 0.9339 | 0.7647 | 0.8229 | 0.4915 | 0.9146 |
| \( e_3 \) | 0.9374 | 0.8840 | 0.8635 | 0.8544 | 0.8978 |

TABLE 5. Consensus index values at cluster level.

| cluster | \( A \) | \( B \) | \( F \) | \( D \) | \( Y \) |
|---------|-------|-------|-------|-------|-------|
| \( A \) | 0.9205 | 0.0000 | 0.8518 | 0.8432 | 0.8415 |
| \( B \) | 0.8659 | 0.7686 | 0.8165 | 0.8521 | 0.8459 |
| \( F \) | 0.0000 | 0.9071 | 0.8763 | 0.0000 | 0.8465 |
| \( D \) | 0.7533 | 0.9141 | 0.0000 | 0.8728 | 0.9096 |
| \( Y \) | 0.8848 | 0.8668 | 0.8464 | 0.8484 | 0.9021 |

The BPA functions are taken into (16), and group evaluation results are obtained, e.g., \( m_{B}^{A}(1;F \rightarrow A) = 0.0273 \), \( m_{Y}^{A}(1;F \rightarrow A) = 0.0845 \), \( m_{Y}^{A}(1;F \rightarrow A) = 0.0066 \), \( m_{Y}^{A}(1;F \rightarrow A) = 0.3693 \), \( m_{Y}^{A}(1;F \rightarrow A) = 0.0893 \), \( m_{Y}^{A}(1;F \rightarrow A) = 0.0291 \), and \( m_{Y}^{A}(1;F \rightarrow A) = 0.3939 \).

*Step 5:* Compute the consensus index at three levels. Similarity degrees between experts and group are computed by (17) and they are set as consensus index values at element level as in Table 4. The consensus index values at cluster level are obtained by (19) and listed in Table 5. The consensus index values at holistic level are obtained by (20) and results are \( CI(1) = 0.7225 \), \( CI(2) = 0.6459 \), \( CI(3) = 0.6138 \).

*Step 6:* Implement consensus reaching in the group ANP.

At holistic level, the knowledge matrices given by expert \( e_1 \) are acceptable since its consensus index value is greater than the consensus threshold \( \gamma = 0.7 \), i.e., \( CI(1) = 0.7225 > 0.7 \). Experts \( e_2 \) and \( e_3 \) both need to modify their knowledge matrices because of \( CI(2) = 0.6459 < 0.7 \) and \( CI(3) = 0.6138 < 0.7 \). The invalid expert set is obtained by (21), i.e., \( ECI = \{2, 3\} \).

At cluster level, four consensus index values of Table 5 corresponding to \( ECI \) are less than threshold \( \gamma = 0.7 \), i.e., \( CI(2;B \rightarrow B) = 0.6475 \), \( CI(2;Y \rightarrow D) = 0.6782 \), \( CI(3;B \rightarrow B) = 0.6517 \), \( CI(3;Y \rightarrow D) = 0.6598 \). Thus the invalid block matrix set is obtained by (22), i.e., \( BCI = \{(2, B \rightarrow B), (2, Y \rightarrow D), (3, B \rightarrow B), (2, Y \rightarrow D)\} \).

At element level, five consensus index values of Table 4 corresponding to \( BCI \) are less than threshold \( \gamma = 0.7 \), i.e., \( CI_{1}^{A}(1;F \rightarrow A) = 0.4117 \), \( CI_{1}^{A}(1;Y \rightarrow D) = 0.5171 \), \( CI_{1}^{A}(1;Y \rightarrow D) = 0.6948 \), \( CI_{1}^{A}(1;B \rightarrow B) = 0.4162 \), \( CI_{1}^{A}(1;Y \rightarrow D) = 0.5304 \). Thus, the invalid knowledge matrix set is obtained by (23), i.e., \( KCI = \{(2, B \rightarrow B, c_3), (2, Y \rightarrow D, c_{16})\} \).
TABLE 7. The supermatrix of the proposed method.

| $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ | $c_6$ | $c_7$ | $c_8$ | $c_9$ | $c_{10}$ |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|
| 0.2431 | 0.1310 | 0.3019 | 0.2120 | 0.0000 | 0.0000 | 0.2980 | 0.4163 | 0.3829 | 0.2433 |
| 0.2479 | 0.4227 | 0.2017 | 0.3155 | 0.0000 | 0.0000 | 0.3645 | 0.2196 | 0.2567 | 0.5018 |
| 0.2994 | 0.3629 | 0.3100 | 0.2956 | 0.0000 | 0.0000 | 0.1780 | 0.2709 | 0.2102 | 0.3026 |
| 0.2176 | 0.1433 | 0.1864 | 0.1792 | 0.0000 | 0.0000 | 0.1596 | 0.0952 | 0.1501 | 0.1525 |
| 0.2898 | 0.4576 | 0.2844 | 0.1828 | 0.3049 | 0.2909 | 0.1677 | 0.2981 | 0.3672 | 0.6344 |
| 0.3403 | 0.2436 | 0.3550 | 0.2690 | 0.4024 | 0.2909 | 0.5220 | 0.3851 | 0.4072 | 0.2592 |
| 0.3708 | 0.2988 | 0.1806 | 0.5482 | 0.2927 | 0.4181 | 0.5103 | 0.3168 | 0.2256 | 0.1064 |
| 0.4000 | 0.0000 | 0.0000 | 0.0000 | 0.1923 | 0.4988 | 0.2192 | 0.5526 | 0.3235 | 0.2635 |
| 0.4000 | 0.0000 | 0.0000 | 0.0000 | 0.4761 | 0.3054 | 0.3408 | 0.2272 | 0.1355 | 0.6082 |
| 0.4000 | 0.0000 | 0.0000 | 0.0000 | 0.3316 | 0.1958 | 0.4400 | 0.2402 | 0.5410 | 0.1261 |
| 0.2407 | 0.1748 | 0.2396 | 0.1952 | 0.2153 | 0.2388 | 0.2647 | 0.0000 | 0.0000 | 0.2194 |
| 0.2888 | 0.2172 | 0.2666 | 0.3101 | 0.2322 | 0.3299 | 0.3115 | 0.0000 | 0.0000 | 0.3207 |
| 0.3085 | 0.2573 | 0.3202 | 0.1731 | 0.2828 | 0.2848 | 0.2888 | 0.0000 | 0.0000 | 0.2843 |
| 0.1619 | 0.3506 | 0.1736 | 0.3216 | 0.2697 | 0.1779 | 0.1851 | 0.0000 | 0.0000 | 0.1755 |
| 0.3730 | 0.3864 | 0.3354 | 0.3991 | 0.2424 | 0.2699 | 0.3506 | 0.2666 | 0.4892 | 0.4767 |
| 0.3386 | 0.4772 | 0.4017 | 0.2632 | 0.4467 | 0.4648 | 0.4185 | 0.4365 | 0.2554 | 0.3085 |
| 0.2884 | 0.1366 | 0.2629 | 0.3376 | 0.3109 | 0.2654 | 0.2308 | 0.2968 | 0.2554 | 0.2148 |

TABLE 8. The weights of block matrices.

| A | B | C | D | Y |
|---|---|---|---|---|
| 0.1241 | 0.0000 | 0.2024 | 0.2449 | 0.1958 |
| 0.3470 | 0.2297 | 0.8381 | 0.3449 | 0.3505 |
| 0.0000 | 0.2113 | 0.0000 | 0.0000 | 0.0126 |
| 0.2156 | 0.2372 | 0.0000 | 0.1325 | 0.1652 |
| 0.3133 | 0.3217 | 0.4444 | 0.2777 | 0.1789 |

Step 7: Construct supermatrix and determine weights of block matrices. We construct the matrix $M$ with $(3;j)\rightarrow j'$ based on the combined block matrices and then compute the matrix $P_{(3;j)\rightarrow j'}$ constructed with pignistic probabilities. We replace $M$ with $P_{(3;j)\rightarrow j'}$, for $j, j' = A, B, F, D, Y$ and get the supermatrix as in Table 7. In addition, we determine the weights of block matrices as listed in Table 8.

Step 8: Construct weighted supermatrix and determine limit weighted supermatrix. The weighted supermatrix is constructed by integrating supermatrix as in Table 7 with the weights of block matrices as in Table 8, then the limit weighted supermatrix is determined by raising the weighted supermatrix to a sufficiently large power.

Step 1: Establish the network structure. The network for determining the marine ecological carrying capacity is constructed as illustrated in Figure 4.

Step 2: Elicit judgments from experts based on pairwise comparisons. The fuzzy pairwise comparative judgment matrices are given by the experts and aggregated with the fuzzy numbers.

Step 9: Calculate overall priorities and rank alternatives. From the limit-weighted supermatrix, the overall priorities of three regions (alternatives) on marine ecological carrying capacity are $c_{15} = 0.0965, c_{16} = 0.1136, c_{17} = 0.0720$. Their corresponding normalized values are $c_{15} = 0.3421, c_{16} = 0.4027, c_{17} = 0.2552$. Thus, the ranking of three regions on marine ecological carrying capacity is $c_{16} > c_{15} > c_{17}$.
TABLE 9. The supermatrix of Michael’s method.

| $c_i$ | $c_j$ | $c_k$ | $c_l$ | $c_m$ | $c_n$ | $c_o$ | $c_p$ |
|-------|-------|-------|-------|-------|-------|-------|-------|
| 0.2357 | 0.2331 | 0.2375 | 0.2371 | 0.0000 | 0.0000 | 0.0000 | 0.2558 |
| 0.2455 | 0.2993 | 0.2221 | 0.2125 | 0.0000 | 0.0000 | 0.0000 | 0.2664 |
| 0.2638 | 0.2143 | 0.2559 | 0.2944 | 0.0000 | 0.0000 | 0.0000 | 0.2322 |
| 0.2550 | 0.2623 | 0.2854 | 0.2560 | 0.0000 | 0.0000 | 0.0000 | 0.2456 |
| 0.3113 | 0.3057 | 0.3051 | 0.2920 | 0.3048 | 0.3068 | 0.2929 | 0.3357 |
| 0.3062 | 0.2895 | 0.3028 | 0.3432 | 0.3550 | 0.3347 | 0.3339 | 0.3072 |
| 0.3824 | 0.4048 | 0.3921 | 0.3648 | 0.3402 | 0.3585 | 0.3753 | 0.3571 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.2802 | 0.3542 | 0.2579 | 0.3334 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.3348 | 0.3260 | 0.3070 | 0.3505 |
| 0.2465 | 0.2452 | 0.2516 | 0.2244 | 0.2152 | 0.2215 | 0.2298 | 0.0000 |
| 0.2728 | 0.2365 | 0.2032 | 0.2223 | 0.2530 | 0.2482 | 0.2687 | 0.0000 |
| 0.2555 | 0.2812 | 0.2775 | 0.2665 | 0.2832 | 0.2807 | 0.2585 | 0.0000 |
| 0.2253 | 0.2371 | 0.2677 | 0.2686 | 0.2486 | 0.2496 | 0.2430 | 0.0000 |
| 0.3417 | 0.3099 | 0.3271 | 0.3591 | 0.2846 | 0.2986 | 0.3098 | 0.2876 |
| 0.2995 | 0.3040 | 0.3566 | 0.5214 | 0.3610 | 0.2985 | 0.3960 | 0.3313 |
| 0.3588 | 0.3861 | 0.3223 | 0.3195 | 0.3544 | 0.3917 | 0.3513 | 0.3833 |

weighted geometric mean as follows.

$$a_{st} = (l_{st}, m_{st}, u_{st}) = \left( \prod_{i=1}^{3} (q_{st})^{w_i}, \prod_{i=1}^{3} (m_{st})^{w_i}, \prod_{i=1}^{3} (u_{st})^{w_i} \right)$$

(28)

In (28), $a_{st} = (l_{st}, m_{st}, u_{st})$ is the comprehensive triangular fuzzy number, $a'_{st} = (l'_{st}, m'_{st}, u'_{st})$ is the triangular fuzzy number given by expert $e_i$, and $w_i$ is the weight of expert $e_i$. Accordingly, we obtain the comprehensive fuzzy judgment matrices of experts as follows.

$$A = (a_{st})_{S \times T}$$

(29)

**Step 3:** Compute the crisp priority vector. Taking the comprehensive fuzzy judgment matrix $A = (a_{st})_{S \times T}$ into (30), its preference priorities $P = (p_s)_{1 \times S}$ can be obtained.

$$\text{max} = \delta$$

$$\kappa_{st} - l_{st} \geq \delta (m_{st} - l_{st})$$

$$\kappa_{st} - l_{st} \geq \delta (m_{st} - l_{st})$$

$$u_{st} - \kappa_{st} \geq \delta (u_{st} - m_{st})$$

$$u_{st} - \kappa_{st} \geq \delta (u_{st} - m_{st})$$

$$\kappa_{st} = p_t / p_t$$

$$\kappa_{st} = p_t / p_s$$

$$\sum_{r} p_r = 1, \quad p_t \geq 0$$

$$\forall s, \quad t; t > s$$

(30)

**Step 4:** Calculate overall priorities and rank alternatives. The supermatrix is constructed as in Table 9, based on which the weighted supermatrix (with weights of block matrices as in Table 8) and the limit-weighted supermatrix is constructed. The normalized overall priorities of three regions on marine ecological carrying capacity are obtained from the limit-weighted supermatrix as $c_{15} = 0.297, c_{16} = 0.335, c_{17} = 0.368$. Accordingly, the ranking of three regions on marine ecological carrying capacity is $c_{17} > c_{16} > c_{15}$.

**C. DISCUSSION**

It is obvious to find that the ranking of three regions on marine ecological carrying capacity derived by the proposed method ($c_{17} > c_{15} > c_{17}$) differs significantly from that derived by Michael’s method ($c_{17} > c_{16} > c_{15}$). Here, we assess the most reasonable ranking on the expert information extraction mechanisms and degree of expert consensus within the group obtained by the two methods. In addition, the respective feasibilities of the methods are considered on the required number of pairwise comparisons. These three aspects are discussed as follows.

1. **Expert information extraction mechanism.** The subjective judgments of experts are used as the inputs of ANP whether in the proposed method or in Michael’s method. In the proposed method, experts give their assessments with knowledge matrices, and each expert only needs to make judgments on those elements that coincide with their particular level of knowledge and experience. In contrast, Michael’s method employs fuzzy pairwise comparative judgment matrices to express the assessments of experts, and each expert must provide all required judgments regardless of their level of knowledge and experience. With the help of the knowledge matrix in the proposed method, each expert only needs to make judgments on the elements that coincide with his/her recognition ability, in other words, he/she is allowed to give nothing for those elements that exceed his/her recognition ability. However, it is unfortunate to find that such the actual recognition ability cannot be reflected in Michael’s method for the reason that each expert has to give all required judgments even though some of them exceed his/her cognitive
ability. Thus, the proposed method avoids the introduction of questionable judgments in the decision-making process, and is therefore a more reasonable approach than Michael’s method on the expert information extraction mechanisms.

(2) Consensus reaching model. The proposed method adopts a reasonably sophisticated appraisal of group consensus based on consensus indices derived at three levels of similarity. In addition, a consensus reaching model is established to enable the experts within the group to reach a high degree of consensus. In contrast, Michael’s method is a static method that does not consider group consensus in the decision-making process. Thus, the application of the group consensus in the proposed method ensures greater uniformity and effectiveness in the decision-making process than Michael’s method, and is therefore a more reasonable approach on the issue of group consensus.

(3) Number of required pairwise comparisons. In the framework of ANP, pairwise comparisons are employed to extract expert judgments whether in the proposed method or in Michael’s method. Such pairwise comparisons are made not only for outer-dependent situations but also for inter-dependent situations. If relevant elements in the two kinds of dependent situations are too many or the number of dependent relationships is too large, then there must be plenty of pairwise comparisons to make. The proposed method could decrease the number of comparisons made in ANP as much as possible, but such an advantage does not exist in Michael’s method. In this numerical example, 342 times of judgments are made for constructing supermatrix in the proposed method, while Michael’s method requires that experts make a total of 954 judgments. This greatly reduced workload provided by the proposed method has two primary benefits. First, this makes the implementation of the proposed method more feasible than that of Michael’s method in practical applications. Second, this helps to ensure that the decisions are more meaningful by avoiding the negative effects of a heavy workload on the judgments of experts. Thus, the method proposed is more feasible than Michael’s method on reducing times of pairwise comparisons.

Therefore, we come to the following conclusion, from the above three aspects of analysis (expert information extraction mechanism, consensus reaching model and times of pairwise comparisons), the results of the proposed method are more reliable than Michael’s method.

V. CONCLUSION

The present study proposed a simplified group analytic network process with consensus reaching denoted as DS/ANP for conducting MCDM analysis. The DS/ANP method was designed to address the four main problems remaining to be solved in the field of group ANP. These include: (1) the exponential growth in the number of pairwise comparison judgments that are required to extract decision information as the number of evaluation criteria/elements increases, (2) the lack of an effective means of addressing the effect of the different levels of knowledge and experience of group members on the quality of decision-making solutions, (3) the lack of a truly effective means of constructing the overall information of a group from the individual judgments of its members, and (4) the lack of addressing conditions of non-consensus among the judgments of expert group members in the decision-making process. A numerical comparison was provided to discuss the reasonableness and feasibility of the proposed method. The main contributions of the present study can be summarized as follows.

Firstly, an expert information extraction mechanism was introduced to simplify the pairwise comparison process in group ANP and reflect the different levels of knowledge and experience of the group members. This addressed problems (1) and (2) by decreasing the number of pairwise comparisons required in group ANP, and increasing the quality of pairwise comparisons by enabling experts to refrain from assigning judgments under conditions where they lacked the requisite knowledge and experience. Secondly, problem (3) was addressed by applying Shafer’s discounting method and Dempster’s rule to effectively construct the overall information of the group in the form of a block matrix, which is the basic unit in ANP. Thirdly, problem (4) was addressed by defining consensus indices at the element level, cluster level, and holistic level in terms of the Jousselme distance to measure the degree of consensus among experts, and a feedback mechanism was implemented to engage experts in an exchange of information toward obtaining greater consensus. Fourthly, the supermatrix obtained in the proposed process was transformed into a supermatrix suitable for use in conventional group ANP based on the pignistic probability. Therefore, the DS/ANP method with consensus reaching was enabled to make effective decisions by following the principles of conventional ANP from supermatrix construction to limit-weighted supermatrix computation.

The proposed method is particularly useful for solving group ANP problems where the scale of the involved experts may be large and their levels of knowledge and experience may be highly diverse. However, the proposed method assumes that the judgments given by experts are crisp values, and it does not consider intuitionistic or hesitant fuzzy environments [23], [56]–[58]. Therefore, we intend in future work to extend the proposed method by applying intuitionistic or hesitant fuzzy sets into the knowledge matrices given by the experts.

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