

Navigation risk assessment scheme based on fuzzy Dempster–Shafer evidence theory

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Abstract

In order to reduce the influence of subjective factors on navigation risk assessment, we present a novel scheme based on the fuzzy Dempster–Shafer evidence theory in this article. At first, we deduce the fuzzy set after analyzing various indicators in actual vessel navigation as an example. What's more, the current data can be adaptively transformed into quantitative information on the basis of two-order membership functions. Considering the inherent defects of standard Dempster–Shafer evidence framework, the assessment process is improved to combine the uncertain and conflicting evidences from available indicators to make reliable decision. Further, three propositions are derived to explain the proposed scheme step by step. Finally, the numerical study results indicate that the proposed scheme has satisfactory performance for vessel navigation risk assessment in the complex waters without any subjective factors.

Keywords

Navigation risk, fuzzy set, D-S evidence theory, indicator, risk level

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Introduction

As a potentially dangerous navigation state, in effect, the navigation risk damages both nature environment and human life. In 2002, the International Maritime Organization (IMO) reported that the vessel navigation risk (VNR) is involved in the likelihood of occurrence and severity of consequence.^{1–3} With the vigorous development of modern transportation, there are plenty of traffic accidents in the complex waters, such as the port, bay, and reservoir. It is necessary to make accurate identification based on the promising assessment scheme. Given that the water traffic is a complex system determined by multifactor, it often involves the intelligent decision-making. Therefore, we should analyze the multi-information and carry out multi-level processing to mine the inherent information as much as possible.

The navigation risk assessment, as an important decision method, is getting more and more accepted to evaluate the risk level. In the past decades, many papers addressing this

research topic have been published in some important journals. First, a fuzzy risk assessment in Akyildiz and Mendes⁴ was incorporated in terms of a set of plausible model scenarios leading to traffic accidents. In view of different navigation conditions, the automatic identification system was implemented as the input for risk assessment under the convention on the international regulations guidelines.⁵ In general, the maneuvers consist of complex dynamics owing to the external environmental conditions, such as the wind, wave, and water depth. In Perera,⁶ a mathematical framework for predicting vessel maneuvers in a short interval was presented. In order to seek the different effects on

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navigation and conduct numerical weather routing system, the representative typhoon was analyzed to make a valuable simulation in Chen et al.⁷ However, the complex structure of operations usually makes the occurrence of traffic accidents inevitable. For minimizing the negative impacts, a particular technique in Kececi and Arslan⁸ was feasible to identify stakeholders responsible in implementing corrective actions. Of course, the situational risk awareness is also crucial for the intelligent decision-making. In Gauss and Rötting,⁹ a navigational risk assessment system was further proposed. Proceeding from the risk-based approach, the aim of Lin and Fang¹⁰ was to identify challenges for operators when preparing for various threats. In view of piloting factors, Hu et al.¹¹ proved a grey assessment model conform the result of subjective judgment with the fuzzy set. In order to enhance the maritime safety, the IMO presented the formal safety assessment method. Liu et al.¹² focused on this method on the vessel navigation, and then took the possible incidents into account. Nowadays, the analytic hierarchy process (AHP) is regarded as a popular assessment method that divides the completed water transportation system into many subsystems. Considering the uncertainty of factors and incompleteness of data, we can get navigation information by using the AHP method. With the comprehensive collection of maritime accident database, Li and Hao¹³ made analysis on the safety risks by combining the AHP with fuzzy set. Hans et al.¹⁴ selected the vessel integrated navigation system as an object, and then applied the AHP method to assess the security. In the AHP model, the weight of risk indicator is calculated by the discriminant matrix owing to the expert experience, where the information is obtained using the associated weights and the consistency test is executed on the basis of discriminant matrix.¹⁵ In this way, the subjective factors play a leading role inevitably. In order to reduce the influence of expert experience in the AHP method, we should improve the assessment schemes and finalize credible results by mining the available information. As we know, the Dempster–Shafer (D-S) evidence theory is an appropriate approach to combine the multi-information.^{16,17} With the dependent basic probabilistic assignment (BPA), the alternative technique for combining evidences was introduced in Blasch et al.¹⁸ Subsequently, Zadeh showed that the use of normalization factor of D-S combination rule on highly conflicting evidence could lead to the counterintuitive results in some cases.¹⁹ On the other hand, the fuzzy logic has its own advantage on the intelligent decision-making, whose solution can be cast in terms that are readily understood. Modeling with the incomplete data, the fuzzy logic gets the connotation through the representation of current information, which is a quantitative technique.^{20,21} For this reason, Wang et al.²² designed a vessel steering control method via the generalized ellipsoidal function-based fuzzy logic. Subject to both fully unknown dynamics and complex input nonlinearities of autonomous vehicle, a Nussbaum-based adaptive fuzzy algorithm was further

proposed in the homogeneity-based finite-time control framework.²³

In this article, it is our intention to solve the dilemmas: How to assess the navigation risk without any interference from subjective factors? How to make a credible decision based on the proposed intelligent scheme? Therefore, we mainly analyze the VNR assessment by combining the fuzzy logic with improved D-S evidence theory, where the innovations of are outlined: (1) the fuzzy set of available indicators is built, and then the current data can be adaptively transformed into quantitative information; (2) the fuzzy assessment matrix is derived based on the enhanced membership function and the entropy of associated weight coefficient; (3) the optimal evidence combination rules are explored to deal with the uncertain and conflicting evidences from various indicators. The remainder of this note is organized as follows: In the “Theory analysis” section, the main navigation indicators are briefly discussed, and then the associated fuzzy sets are presented. In the “Innovative assessment scheme” section, the proposed scheme is discussed with the innovative propositions in detail. Subsequently, the numerical studies are presented with results to analyze the overall performance of proposed scheme in the “Numerical study and discussion” section. Finally, we come to the conclusion with the next research plan in the “Conclusion” section.

Theory analysis

In this section, we briefly analyze the indicators of vessel navigation,^{24,25} and then present the associated fuzzy set.

Navigation indicator

The primary indicators of water traffic includes three categories: the hydrological–meteorological indicator, natural environmental indicator, and navigable condition indicator.

Taking into account the enormously increasing probability of traffic accidents in bad weather, we consider the secondary indicators during the whole process, that is, the visibility, wind, wave, and current. It is generally known that the water traffic is affected by the poor visibility. Regarding the course and speed of vessels, the wind speed is an increasing probability function of water traffic accident, and the wave and current can cause vessel collision in channel. Therefore, we choose the visible distance of route as a standard to measure the visibility level. The wind speed, wave speed, and current speed are used as the levels of wind, wave, and current.

In view of natural environment, the vessel operator should comprehensively judge the water length, water depth, and obstacle width. The longer the channel length, the larger the probability of water traffic accident. With the increase of water resistance in the shallow region, the vessel power gradually decreases. Also, the narrow channel increases the probability of encounters. Inevitably, the

Table 1. Assessment standard for indicator.

Indicator		Risk level μ_{ji}^k				
Primary indicator, X_j	Secondary indicator, x_{ji}	Trivial, μ_{ji}^1	Tolerable, μ_{ji}^2	Moderate, μ_{ji}^3	Substantial, μ_{ji}^4	Intolerable, μ_{ji}^5
Hydrology and meteorology, X_1	Visibility, x_{11} (km)	>50	50 ~ 10	10 ~ 2	2 ~ 0.5	<0.5
	Wind, x_{12} (m/s)	<1.6	1.6 ~ 8	8 ~ 13.9	13.9 ~ 20.8	>20.8
	Wave, x_{13} (knot)	<3	3 ~ 4	4 ~ 5	5 ~ 6	>6
	Current, x_{14} (knot)	<1.5	1.5 ~ 2.5	2.5 ~ 4	4 ~ 6	>6
Nature environment, X_2	Channel length, x_{21} (km)	<25	25 ~ 90	90 ~ 155	155 ~ 200	>200
	Depth/draft, x_{22}	>4.0	4.0 ~ 2.0	2.0 ~ 1.6	1.6 ~ 1.2	<1.2
	Channel width/vessel width, x_{23}	>8	8 ~ 5	5 ~ 3	3 ~ 2	<2
	Obstacle size, x_{24} (m)	<25	25 ~ 50	50 ~ 100	100 ~ 200	>200
Navigable condition, X_3	Management rate, x_{31} (%)	>95	95 ~ 90	90 ~ 80	80 ~ 70	<70
	Channel intersections, x_{32}	<2	2 ~ 3	3 ~ 5	5 ~ 8	>8
	Vessel density, x_{33} (vessel/km ²)	<5	5 ~ 10	10 ~ 20	20 ~ 25	>25
	Vessel chasing, x_{34} (vessel)	<2	2 ~ 5	5 ~ 15	15 ~ 25	>25

obstacles are also the inherent harm. Then, we select the channel length, ratio of water depth to draft, ratio of channel width to vessel width, and obstacle size as the assessment standard.

Navigable condition includes the natural and artificial background, where the traffic management rate, channel crossing, vessel density, and chasing are the secondary indicators. Most of all, the navigable facilities are essential. The crossing channels increase the probability of vessel encounters, that is, the larger the number of vessels in unit waters, the greater the accident likelihood. Further, the chasing situation may cause collision. We use the navigable facilities to assess the management rate. The channel situation is measured with the channel intersections. As for vessels, their number in unit waters and chasing ratio are regarded as the assessment standard.

Fuzzy set of VNR

The IMO navigation rulemaking requires five risk levels ($k = 1, 2, 3, 4, 5$) to assess the VNR in the complex waters,^{1,3,24} which are the trivial risk, tolerable risk, moderate risk, substantial risk, and intolerable risk. According to the substantial analysis and statistics on the navigation

factors, the primary indicator X_j ($j = 1, 2, 3$) and the corresponding secondary indicators x_{ji} ($i = 1, 2, 3, 4$) are cited in Table 1, where the viability x_{11} , ratio of depth to draft x_{22} , ratio of channel width to vessel width x_{23} , and traffic management rate x_{31} are the benefit-type indicators. In other words, the greater the value, the better the performance. By comparison, other secondary indicators follow the cost-type distribution, which should be assigned the small value.

Innovative assessment scheme

This section derives the proposed assessment scheme by combining the fuzzy logic with enhanced D-S evidence theory.

Principle of proposed scheme

Due to the uncertain and insufficient information, the fuzzy set has no fixed representation. We suppose that the fuzzy set is based on the fuzzy comprehensive cluster, where the inputs are mapped by the membership functions, and the starting and ending points have large information content^{26–29}

$$\mu = f(x) = \begin{cases} \left(\frac{x-b}{c-b} \right)^\kappa & b \leq x \leq c \\ \left(\frac{b-x}{b-a} \right)^\kappa & a \leq x \leq b \\ 0; (1) & x \leq a, x \geq c; \text{ (when } a \text{ is the minimum value or } c \text{ is the maximum value)} \end{cases} \quad (1)$$

where the power κ is often taken to 1, 2, and 3. The fuzzy set has the simplest linear type under the condition of

$\kappa = 1$. In this note, we use $\kappa = 2$ to represent the characteristics of uncertain information. Figure 1 indicates the

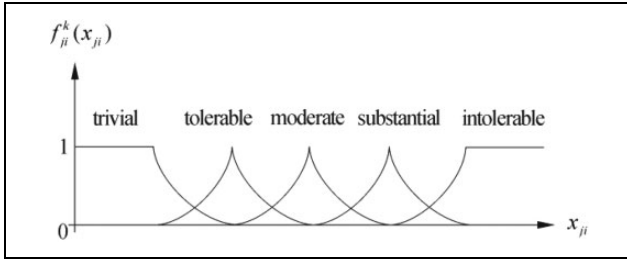


Figure 1. Risk level and its fuzzy set.

relationship between the indicator x_{ji} and its function $f_{ij}^k(x_{ij})$. Note that the maximal value of $f_{ij}^k(x_{ij})$ is 1, and the rising and trailing edges follow the nonlinear distribution.

For example, we only derive the risks based on x_{11} to define the membership functions. Further, $f_{ij}^k(\cdot)$ is reduced to the form $f_{ij}^k[\cdot, \cdot, \cdot]$, where the middle element is the crossing point between two adjacent curves. Then, Table 2 gives the membership function of 12 secondary indicators after our statistics

$$\mu_{11}^1 = f_{11}^1(x_{11}) = \begin{cases} 1 & x_{11} \geq 50 \\ \left(\frac{50 - x_{11}}{20}\right)^2 & 30 \leq x_{11} \leq 50 \\ 0 & x_{11} \leq 30 \end{cases} \quad (2)$$

$$\mu_{11}^2 = f_{11}^2(x_{11}) = \begin{cases} \left(\frac{x_{11} - 30}{20}\right)^2 & 30 \leq x_{11} \leq 50 \\ \left(\frac{30 - x_{11}}{24}\right)^2 & 6 \leq x_{11} \leq 30 \\ 0 & x_{11} \leq 6, x_{11} \geq 50 \end{cases}$$

$$\mu_{11}^3 = f_{11}^3(x_{11}) = \begin{cases} \left(\frac{x_{11} - 6}{24}\right)^2 & 6 \leq x_{11} \leq 30 \\ \left(\frac{6 - x_{11}}{4.75}\right)^2 & 1.25 \leq x_{11} \leq 6 \\ 0 & x_{11} \leq 1.25, x_{11} \geq 30 \end{cases} \quad (4)$$

$$\mu_{11}^4 = f_{11}^4(x_{11}) = \begin{cases} \left(\frac{x_{11} - 1.25}{4.75}\right)^2 & 1.25 \leq x_{11} \leq 6 \\ \left(\frac{1.25 - x_{11}}{0.75}\right)^2 & 0.5 \leq x_{11} \leq 1.25 \\ 0 & x_{11} \leq 1.25, x_{11} \geq 6 \end{cases} \quad (5)$$

$$\mu_{11}^5 = f_{11}^5(x_{11}) = \begin{cases} 0 & x_{11} \geq 1.25 \\ \left(\frac{x_{11} - 0.5}{0.75}\right)^2 & 0.5 \leq x_{11} \leq 1.25 \\ 1 & x_{11} \leq 0.5 \end{cases} \quad (6)$$

For simplicity, the membership function μ_{11}^k is illustrated by the example of the visibility $x_{11} = 32$ km in Table 3. Note that the referenced methods^{24,25} only give the result with the linear estimation. As a result, the interference component μ_{11}^2 is relatively large. By comparison, the proposed scheme reduces μ_{11}^2 by using the two-order approximation. Regarding the uncertain and conflicting evidences, the extended component μ_{11}^0 can be solved in the proposed D-S framework.

(3) **Proposition 1.** Given that the membership function μ_{ji}^k ($1 \leq j \leq q, 1 \leq i \leq n, 0 \leq k \leq p$) represents the risk

Table 2. Membership function of secondary indicators.

Indicator		μ_{ji}^1	μ_{ji}^2	μ_{ji}^3	μ_{ji}^4	μ_{ji}^5
X_1	x_{11}	$f_{11}^1[30, 50, -]$	$f_{11}^2[6, 30, 50]$	$f_{11}^3[1.25, 6, 30]$	$f_{11}^4[0.5, 1.25, 6]$	$f_{11}^5[-, 0.5, 1.25]$
	x_{12}	$f_{12}^1[-, 1.6, 4.8]$	$f_{12}^2[1.6, 4.8, 10.95]$	$f_{12}^3[4.8, 10.95, 17.35]$	$f_{12}^4[10.95, 17.35, 20.8]$	$f_{12}^5[17.35, 20.8, -]$
	x_{13}	$f_{13}^1[-, 3, 3.5]$	$f_{13}^2[3, 3.5, 4.5]$	$f_{13}^3[3.5, 4.5, 5.5]$	$f_{13}^4[4.5, 5.5, 6]$	$f_{13}^5[5.5, 6, -]$
	x_{14}	$f_{14}^1[-, 1.5, 2]$	$f_{14}^2[1.5, 2, 3.25]$	$f_{14}^3[2, 3.25, 5]$	$f_{14}^4[3.25, 5, 6]$	$f_{14}^5[5, 6, -]$
X_2	x_{21}	$f_{21}^1[-, 25, 57.5]$	$f_{21}^2[25, 57.5, 122.5]$	$f_{21}^3[57.5, 122.5, 177.5]$	$f_{21}^4[122.5, 177.5, 200]$	$f_{21}^5[177.5, 200, -]$
	x_{22}	$f_{22}^1[3, 4, -]$	$f_{22}^2[1.8, 3, 4]$	$f_{22}^3[1.4, 1.8, 3]$	$f_{22}^4[1.2, 1.4, 1.8]$	$f_{22}^5[-, 1.2, 1.4]$
	x_{23}	$f_{23}^1[6.5, 8, -]$	$f_{23}^2[4, 6.5, 8]$	$f_{23}^3[2.5, 4, 6.5]$	$f_{23}^4[2, 2.5, 4]$	$f_{23}^5[-, 2, 2.5]$
	x_{24}	$f_{24}^1[-, 25, 37.5]$	$f_{24}^2[25, 37.5, 75]$	$f_{24}^3[37.5, 75, 150]$	$f_{24}^4[75, 150, 200]$	$f_{24}^5[150, 200, -]$
X_3	x_{31}	$f_{31}^1[92.5, 95, -]$	$f_{31}^2[85, 92.5, 95]$	$f_{31}^3[75, 85, 92.5]$	$f_{31}^4[70, 75, 80]$	$f_{31}^5[-, 70, 75]$
	x_{32}	$f_{32}^1[-, 2, 2.5]$	$f_{32}^2[2, 2.5, 4]$	$f_{32}^3[2.5, 4, 6.5]$	$f_{32}^4[4, 6.5, 8]$	$f_{32}^5[6.5, 8, -]$
	x_{33}	$f_{33}^1[-, 5, 7.5]$	$f_{33}^2[5, 7.5, 15]$	$f_{33}^3[7.5, 15, 22.5]$	$f_{33}^4[15, 22.5, 25]$	$f_{33}^5[22.5, 25, -]$
	x_{34}	$f_{34}^1[-, 2, 3.5]$	$f_{34}^2[2, 3.5, 10]$	$f_{34}^3[3.5, 10, 20]$	$f_{34}^4[10, 20, 25]$	$f_{34}^5[20, 25, -]$

Table 3. Membership function of visibility.

Method	μ_{11}^1	μ_{11}^2	μ_{11}^3	μ_{11}^4	μ_{11}^5	μ_{11}^0
Referenced method	0.9000	0.1000	0	0	0	0
Proposed scheme	0.8100	0.0100	0	0	0	0.1800

level of secondary indicator x_{ji} , its normalized weight w_{ji} in the fuzzy set can be computed as

$$w_{ji} = \frac{\sum_{k=0}^p \mu_{ji}^k \sum_{j=1}^q \sum_{i=1}^n \mu_{ji}^k}{\sum_{j=1}^q \sum_{i=1}^n \left(\sum_{k=0}^p \mu_{ji}^k \sum_{j=1}^q \sum_{i=1}^n \mu_{ji}^k \right)} \quad (7)$$

Proof. The information entropy is defined as the averaged information content produced by a stochastic source. The information entropy fully takes into account the probability of achieving a specific indicator, so the information is about the underlying probability distribution. Given that rarer indicators provide more information, the information entropy should quantify the considerations when a probability distribution of the source information is unknown. We use $\log_2 w$ to represent the variable that takes the value of w . Considering the information entropy $H(w_{ji})$ of normalized weight w_{ji} ($w_{ji} \geq 0$), we have in hand the following equations

$$\begin{cases} H(w_{ji}) = -\sum_{j=1}^q \sum_{i=1}^n w_{ji} \log_2 w_{ji} \\ \text{s.t. } \sum_{j=1}^q \sum_{i=1}^n w_{ji} = 1 \end{cases} \quad (8)$$

In the usual optimization, the method of Lagrange multiplier is a strategy for finding the local maxima or minima of a nonlinear function subject to equality constraints. Further, the Lagrange multiplier is a mathematical tool without the need to explicitly solve the conditions and utilize them to eliminate extra variables. Suppose that λ is the Lagrange multiplier, then the Lagrange function of w_{ji} can be structured as

$$L(w_{ji}, \lambda) = -\sum_{j=1}^q \sum_{i=1}^n w_{ji} \log_2 w_{ji} + \lambda \left(\sum_{j=1}^q \sum_{i=1}^n w_{ji} - 1 \right) \quad (9)$$

We define that $L(w_{ji}, \lambda)$ has continuously one-partial derivatives and set the above equation derivations to 0

$$\begin{cases} \frac{\partial L}{\partial w_{ji}} = \log_2 w_{ji} + 1 - \lambda = 0 \\ \frac{\partial L}{\partial \lambda} = \sum_{j=1}^q \sum_{i=1}^n w_{ji} - 1 = 0 \end{cases} \quad (10)$$

After solving the mentioned equations, we can obtain the optimal solution $w_{ji, \text{OP}}$ as

$$w_{ji, \text{OP}} = \frac{1}{qn} \quad (11)$$

Note that $H(w_{ji})$ reaches the maximum in the case of equivalent w_{ji} . Regarding the uncertainty of μ_{ji}^k , we compute the mathematical expectation of $\bar{\mu}_{ji}^k$ as follows

$$\begin{aligned} \bar{\mu}_{ji}^k &= w_{ji, \text{OP}} \sum_{j=1}^q \sum_{i=1}^n \mu_{ji}^k \\ &= \frac{1}{qn} \left[(\mu_{11}^k + \mu_{12}^k + \cdots + \mu_{1n}^k) + \cdots + (\mu_{q1}^k + \mu_{q2}^k + \cdots + \mu_{qn}^k) \right] \end{aligned} \quad (12)$$

Let $[\cdot]^T$ be the transposed matrix, we use the correlation coefficient r_{ji} to define the similarity between μ_{ji}^k and $\bar{\mu}_{ji}^k$

$$\begin{aligned} r_{ji} &= \sum_{k=0}^p \mu_{ji}^k \bar{\mu}_{ji}^k \\ &= [\mu_{ji}^1 \quad \mu_{ji}^2 \quad \cdots \quad \mu_{ji}^p \quad \mu_{ji}^0] [\bar{\mu}_{ji}^1 \quad \bar{\mu}_{ji}^2 \quad \cdots \quad \bar{\mu}_{ji}^p \quad \bar{\mu}_{ji}^0]^T \end{aligned} \quad (13)$$

Therefore, the normalized weight w_{ji} can be written as

$$w_{ji} = \frac{r_{ji}}{\sum_{j=1}^q \sum_{i=1}^n r_{ji}} \quad (14)$$

Note that w_{ji} is mainly depended on r_{ji} . The larger the value of w_{ji} , the better the approximation performance. Substituting equations (12) and (13) into equation (14), we can get w_{ji} defined in equation (7). Although $w_{ji, \text{OP}}$ and $\bar{\mu}_{ji}^k$ are used in the above recursion, μ_{ji}^k is only the factor that affects w_{ji} .

After obtaining w_{ji} , we obtain the fuzzy matrix G

$$G = \begin{bmatrix} w_{11}\mu_{11}^1 & w_{11}\mu_{11}^2 & \cdots & w_{11}\mu_{11}^p & w_{11}\mu_{11}^0 \\ w_{12}\mu_{12}^1 & w_{12}\mu_{12}^2 & \cdots & w_{12}\mu_{12}^p & w_{12}\mu_{12}^0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{qn}\mu_{qn}^1 & w_{qn}\mu_{qn}^2 & \cdots & w_{qn}\mu_{qn}^p & w_{qn}\mu_{qn}^0 \end{bmatrix} \quad (15)$$

As we know, the D-S evidence theory is a general reasoning framework. It is bounded by both belief and plausibility, where the belief in a hypothesis is constituted by the sum of masses in all sets. The plausibility equals 1 minus the sum of masses in all sets whose intersection with the hypothesis is empty. It is an upper bound on the possibility that the hypothesis is true.³⁰ Then, we use the BPA in the space \mathcal{O} to define the belief for one evidence on the probabilities for a related evidence. The BPA is updated when a new evidence is available based on the combination rule. Therefore, the BPA $m : 2^{\mathcal{O}} \rightarrow [0, 1]$ can be written as

$$\begin{cases} \sum_{k=0}^p m_{ji}(A^k) = 1 & 0 \leq m_{ji}(A^k) \leq 1 \\ m_{ji}(\Phi) = 0 \end{cases} \quad (16)$$

Note that the normalized $m_{ji}(A^k)$ reflects the occurrence probability of one-point subset A^k , and the ratio of $w_{ji}\mu_{ji}^k$ to the sum of corresponding line $\sum_{k=0}^p w_{ji}\mu_{ji}^k$ defines $m_{ji}(A^k)$

$$m_{ji}(A^k) = \frac{w_{ji}\mu_{ji}^k}{\sum_{k=0}^p w_{ji}\mu_{ji}^k} \quad (17)$$

Therefore, the BPA matrix M is given by

$$M = \begin{bmatrix} m_{11}(A^1) & m_{11}(A^2) & \cdots & m_{11}(A^p) & m_{11}(A^0) \\ m_{12}(A^1) & m_{12}(A^2) & \cdots & m_{12}(A^p) & m_{12}(A^0) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ m_{qn}(A^1) & m_{qn}(A^2) & \cdots & m_{qn}(A^p) & m_{qn}(A^0) \end{bmatrix} \quad (18)$$

where each element in one line has been normalized.

Suppose that $\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k)$ and

$\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k)$ are the belief and plausible,

respectively, according to the D-S evidence combination rule, the combined BPA of the secondary indicators can be written as^{19,31–33}

$$m(A^k) = \frac{\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k)}{\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k)} \quad (19)$$

Note that $m(A^k)$ becomes more unstable when there is

$\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k) = 0$. In order to overcome the inherent defects in the standard D-S evidence combination rule, we present proposition 2 as follows:

Proposition 2. Suppose that there exists the exceptional case $m_{ji}(A^{k_0}) = 0$ in the BPA matrix M , then its value can be updated as

$$m_{ji}(A^{k_0}) = \varepsilon \quad \varepsilon > 0 \quad (20)$$

where the threshold of BPA is taken to $\varepsilon > 0$.

Proof. In equation (19), it is obvious that

$\sum_{k=0}^p \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^k) = 0$ when the exceptional term is $m_{ji}(A^k) = 0$. According to the D-S evidence combination rule, the normal reasoning result may become incredible. Therefore, we suppose that $\max\{m_{ji}(A^k)\}$ is the maximal BPA in the same line corresponding to $m_{ji}(A^{k_0}) = 0$, then the $\max\{m_{ji}(A^k)\}$ can be divided into two components

$$\begin{cases} \max\{m_{ji}(A^k)\} - \varepsilon \\ \varepsilon \end{cases} \quad (21)$$

Note that the threshold of BPA ε should be set assigned in the practical applications. After reassigning the related BPAs, the sum of elements in each line is equal to 1. We adaptively update $\max\{m_{ji}(A^k)\}$ when the total number of 0s is γ

$$\begin{cases} \max\{m_{ji}(A^k)\} - \gamma\varepsilon \\ \varepsilon \end{cases} \quad (22)$$

□

The belief is usually converted to the Bayesian belief and turns assigning the BPA for sets.^{34,35} If there are some conflicting evidences or the conclusion is not accord with the common sense, it cannot effectively combine the evidences

$$\begin{cases} \sum_{k=1}^p m_{ji}(A^k) \leq 1 & 0 \leq m_{ji}(A^k) \leq 1 \\ m_{ji}(\Phi) = 0 \end{cases} \quad (23)$$

Therefore, we continue to adjust the BPAs of some elements in \mathcal{O} for the uncertain situation

$$m_{ji}(A^0) = 1 - \sum_{k=1}^p m_{ji}(A^k) \quad (24)$$

Proposition 3. Suppose that $m_{ji}^N(A^k)$ ($k = 1, \dots, p$) is the modified BPA, then we have the enhanced D-S combination rule based on $\chi = q \times n$ secondary indicators

$$\begin{cases} m(A^k) = \frac{m_{ji}^N(A^k)}{\sum_{k=1}^p m_{ji}^N(A^k) + \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0)} \\ m(A^0) = \frac{\prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0)}{\sum_{k=1}^p m_{ji}^N(A^k) + \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0)} \end{cases} \quad (25)$$

Table 4. Pseudo-code of proposed assessment scheme.

1. Input the secondary indicators.
2. Compute the risk degree μ_{ij}^k using its fuzzy set $f_{ij}^k(\cdot)$ based on Table 2.
3. Compute the normalized weight w_{ji} using equation (7).
4. Construct the fuzzy assessment matrix G using equation (15).
5. Compute the BPA $m_{ji}(A^k)$ using equation (17).
6. Construct the BPA matrix M using equation (18).
7. If there exists $m_{ji}(A^{k_0}) = 0$, compute the related BPAs using equation (22).
8. If there exists $\sum_{k=1}^p m_{ji}(A^k) \leq 1$, compute the combined BPAs using equation (25).
9. Report the final assessment results.

BPA: basic probabilistic assignment.

where $m_{ji}^N(A^k)$ is given by

$$m_{ji}^N(A^k) = \begin{cases} \left(m_{ji}(A^k) + m_{ji}(A^0)\right)m_{j(i-1)}^N(A^k) + m_{ji}(A^k) \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0) & i \geq 2, j \geq 1 \\ \left(m_{ji}(A^k) + m_{ji}(A^0)\right)m_{(j-1)n}^N(A^k) + m_{ji}(A^k) \prod_{j=2}^q \prod_{i=1}^n m_{(j-1)n}(A^0) & i = 1, j \geq 2 \\ m_{11}(A^k) & i = 1, j = 1 \end{cases} \quad (26)$$

Proof. In equation (24), the value of BPA should be the single element in \mathcal{O} as well as A^0 itself. Then, $m_{ji}^N(A^k)$ can be rewritten as

$$\begin{aligned} m_{ji}^N(A^k) &= \left(m_{ji}(A^k) + m_{ji}(A^0)\right)m_{j(i-1)}^N(A^k) + m_{ji}(A^k) \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0) \\ &= \left(m_{ji}(A^k) + m_{ji}(A^0)\right) \left(m_{j(i-1)}^N(A^k) + \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0)\right) - m_{ji}(A^0) \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0) \\ &= \left(m_{ji}(A^k) + m_{ji}(A^0)\right) \left(\left(m_{j(i-1)}(A^k) + m_{j(i-1)}(A^0)\right) \left(m_{j(i-2)}^N(A^k) + \prod_{j=1}^q \prod_{i=3}^n m_{j(i-2)}(A^0)\right) \right. \\ &\quad \left. - \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0) + \prod_{j=1}^q \prod_{i=2}^n m_{j(i-1)}(A^0) \right) - \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0) \\ &= \left(m_{ji}(A^k) + m_{ji}(A^0)\right) \left(m_{j(i-1)}(A^k) + m_{j(i-1)}(A^0)\right) \left(m_{j(i-2)}^N(A^k) + \prod_{j=1}^q \prod_{i=3}^n m_{j(i-2)}(A^0)\right) - \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0) \\ &= \left(m_{ji}(A^k) + m_{ji}(A^0)\right) \left(m_{j(i-1)}(A^k) + m_{j(i-1)}(A^0)\right) \cdots \left(m_{(j-1)i}(A^k) + m_{(j-1)i}(A^0)\right) \cdots \left(m_{11}(A^k) + m_{11}(A^0)\right) \\ &\quad - \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0) \\ &= \prod_{j=1}^q \prod_{i=1}^n \left(m_{ji}(A^k) + m_{ji}(A^0)\right) - \prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0) \end{aligned} \quad (27)$$

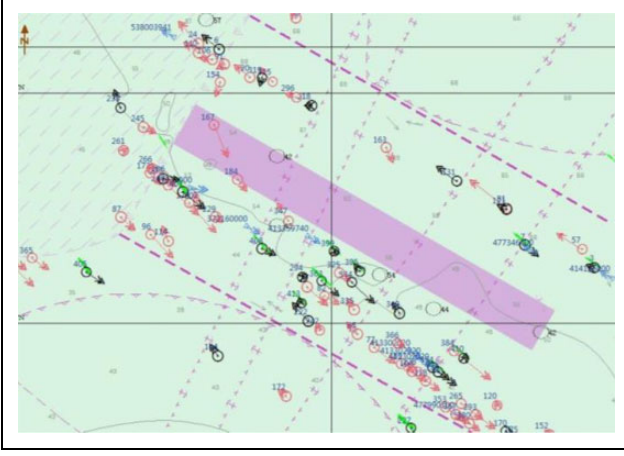


Figure 2. Main channel of Dalian.

Note that the numerator in equation (19) can be presented by equation (27), which takes into account the uncertain situation given by equation (24). We compute the sum of $\sum_{k=0}^p m_{ji}^N(A^k)$ and $\prod_{j=1}^q \prod_{i=1}^n m_{ji}(A^0)$, then the denominator in equation (19) can be easily replaced. Further, the representation of $m(A^0)$ in equation (25) is supplemented when the sum of the total BPAs equals 1

$$\sum_{k=0}^p m(A^k) = 1 \quad (28)$$

□

Remark 1. Let $O(\cdot)$ be the computational complexity, then the complexity of 1 evidence based on proposition 3 is the number of elements $|\mathcal{O}|$, that is, $O(|\mathcal{O}|)$. Comparison with the computational complexity of standard D-S evidence theory^{30,33,34} $O(2^{|\mathcal{O}|})$, it is obvious that the proposed scheme has the linear transformation. With the increase of $|\mathcal{O}|$, the proposed scheme drastically reduces the computational complexity.

Implementation of proposed scheme

With respect to all the secondary indicators, Table 4 presents the pseudo-code of proposed scheme. In step 2, the

membership function μ_{ij}^k is comprehensively computed based on Tables 1 and 2. According to proposition 1, the corresponding weight w_{ji} is computed in step 3. By constructing the fuzzy assessment matrix G , the BPA $m_{ji}(A^k)$ and its matrix M are obtained in steps 4 to 6. After analyzing the BPAs in M , we apply propositions 2 and 3 to combine the BPAs when $m_{ji}(A^{k_0}) = 0$ or $\sum_{k=1}^p m_{ji}(A^k) \leq 1$ in steps 7 and 8. At last, the decisions are reported in step 9.

Numerical study and discussion

In this scenario, we make the numerical experiment to verify the assessment performance of proposed scheme. Given that the available secondary indicators have limitation and uncertainty, the proposed scheme is used to make intelligent decision. Our experimental environment was: IntelTM CoreTM i5, RAM 4 GB, MicrosoftTM WindowsTM 7, and MATLABTM V8.4. Twelve indicators refer to the visibility, wind, wave, current, channel length, ratio of depth to draft, ratio of channel width to vessel width, obstacle size, management rate, channel intersections, vessel density, and vessel chasing. Correspondingly, the related parameters are set as $q = 3$, $n = 4$, and $p = 5$.

Figure 2 demonstrates the main channel of Dalian, and Table 5 gives the detailed characteristics of this channel and a tested liner. We can compute that the ratio of depth to draft is 1.34 and the ratio of channel width to vessel width is 8.44. After getting all secondary indicators, we use equation (2) and Table 2 to get the membership function in Table 6.

Note that the information of the former five columns represents five levels of assessment risks, where x_{12} , x_{14} , and x_{32} are the components that mainly support the “moderate” risk, and x_{21} represents the risk level is “substantial”. Therefore, they are conflicting with other indicators. Further, the data of the last column denote the remainder risk (uncertain situation) that doesn’t belong to any level owing to the characteristics of required quadratic curve. As seen, some values in this column are unequal to 0, especially the value of x_{32} is maximal, which defines there is uncertainty among them. To a certain extent, the

Table 5. Related parameters.

	Visibility	Wind	Wave	Current
Hydrology and meteorology	32 km	11.7 m/s	3.1 knot	3 knot
Nature environment	Channel depth 10 m	Channel width 270 m	Channel length 2.5 km	Obstacle size 15 m
Navigable condition	Management perfect rate 97%	Number of channel intersections 5	Vessel density 1.5 (vessel/km ²)	Vessel chasing 1.2 (vessel)
Vessel characteristics	Vessel length 264 m	Vessel width 32 m	Vessel draft 7.46 m	

Table 6. Membership function.

Indicators	μ_{ji}^1	μ_{ji}^2	μ_{ji}^3	μ_{ji}^4	μ_{ji}^5	μ_{ji}^0
x_{11}	0.8100	0.0100	0.0000	0.0000	0.0000	0.1800
x_{12}	0.0000	0.0000	0.7793	0.0137	0.0000	0.2069
x_{13}	0.6400	0.0400	0.0000	0.0000	0.0000	0.3200
x_{14}	0.0000	0.0400	0.6400	0.0000	0.0000	0.3200
x_{21}	0.0000	0.0000	0.0000	0.4900	0.0900	0.4200
x_{22}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
x_{23}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
x_{24}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
x_{31}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
x_{32}	0.0000	0.0000	0.3600	0.1600	0.0000	0.4800
x_{33}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
x_{34}	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000

uncertain situation also causes $\sum_{k=1}^p m_{ji}(A^k) \leq 1$. At this time, we substitute the membership function into equation (7), then the normalized weight can be written as

$$w_{ji} = \begin{bmatrix} 0.1016 & 0.0286 & 0.0857 & 0.0280 & 0.0182 \\ 0.1186 & 0.1186 & 0.1186 & 0.1186 & 0.0266 \\ 0.1186 & 0.1186 & & & \end{bmatrix}^T \quad (29)$$

Regarding equation (15), we get the fuzzy assessment matrix G based on μ_{ji}^k and w_{ji}

$$G = \begin{bmatrix} 0.0823 & 0.0100 & 0.0000 & 0.0000 & 0.0000 & 0.0183 \\ 0.0000 & 0.0000 & 0.0223 & 0.0004 & 0.0000 & 0.0059 \\ 0.0549 & 0.0034 & 0.0000 & 0.0000 & 0.0000 & 0.0274 \\ 0.0000 & 0.0011 & 0.0179 & 0.0000 & 0.0000 & 0.0090 \\ 0.0000 & 0.0000 & 0.0000 & 0.0089 & 0.0016 & 0.0076 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0096 & 0.0043 & 0.0000 & 0.0128 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \\ 0.1186 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \end{bmatrix} \quad (30)$$

Given that many 0s are in equation (30), there will be some BPAs in the matrix M by using equation (17). After

setting the threshold $\varepsilon = 0.0020$ and the number of 0s in each row

$$\gamma_{ji} = [3 \ 3 \ 3 \ 3 \ 3 \ 5 \ 5 \ 5 \ 5 \ 3 \ 5 \ 5]^T \quad (31)$$

we can update the related BPAs based on equation (22). Therefore, the BPA matrix M becomes

$$M = \begin{bmatrix} 0.8037 & 0.0100 & 0.0020 & 0.0020 & 0.0020 & 0.1803 \\ 0.0020 & 0.0020 & 0.7722 & 0.0137 & 0.0020 & 0.2081 \\ 0.6344 & 0.0400 & 0.0020 & 0.0020 & 0.0020 & 0.3196 \\ 0.0020 & 0.0400 & 0.6338 & 0.0020 & 0.0020 & 0.3202 \\ 0.0020 & 0.0020 & 0.0020 & 0.4866 & 0.0869 & 0.4205 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.0020 & 0.0020 & 0.3600 & 0.1600 & 0.0020 & 0.4740 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.9900 & 0.0020 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \end{bmatrix} \quad (32)$$

With respect to equation (25), the combined BPAs are achieved based on the enhanced D-S evidence combination rule

$$\begin{cases} m(A^k) = [0.9999 & 0.0000 & 0.0000 & 0.0000 & 0.0000] \\ m(A^0) = 0.0001 \end{cases} \quad (33)$$

Note that the largest $m(A^1)$ means the current navigation risk is the “trivial” level, which is in accordance with fact. In the same scenario, we achieve the comparison results of standard D-S evidence theory, AHP method,¹⁵ neural network³⁶ and proposed scheme under 100 trails in Table 7. As seen, the standard D-S evidence theory uses the infinite “NaN” as the result. The reason can be explained that the different BPAs may lead to extremely unstable fusion results. Only some BPAs are taken to zero, the standard D-S method makes the unreasonable decision owing to the uncertain and conflicting evidences. The AHP method needs the expert experience to compute the coefficient of consistency ratio. Then, the “trivial” risk assessment result can be obtained whereas the “moderate” risk result is in the second order. Through survey, the subjective factors of

Table 7. Comparison of averaged assessment accuracy.

Assessment method	Trivial	Tolerable	Moderate	Substantial	Intolerable	Uncertain
Standard D-S method	NaN	NaN	NaN	NaN	NaN	0
AHP method	0.9574	0.0318	0.0108	0	0	0
Neural network	0.9703	0.0236	0.0061	0	0	0
Proposed scheme	0.9996	0.0002	0.0001	0	0	0.0001

D-S: Dempster–Shafer; AHP: analytic hierarchy process.

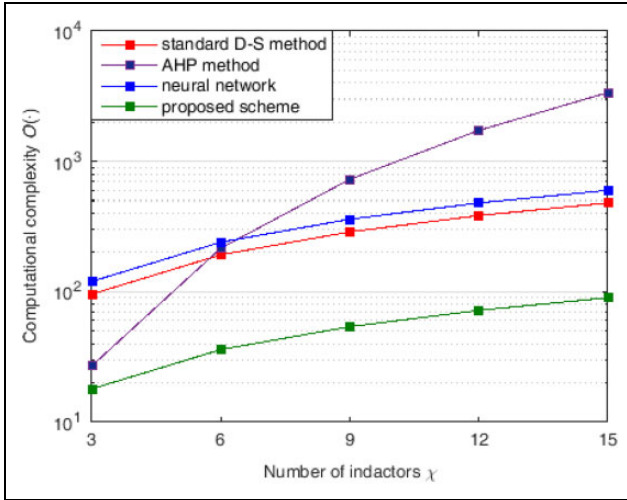


Figure 3. Computational complexity under different χ .

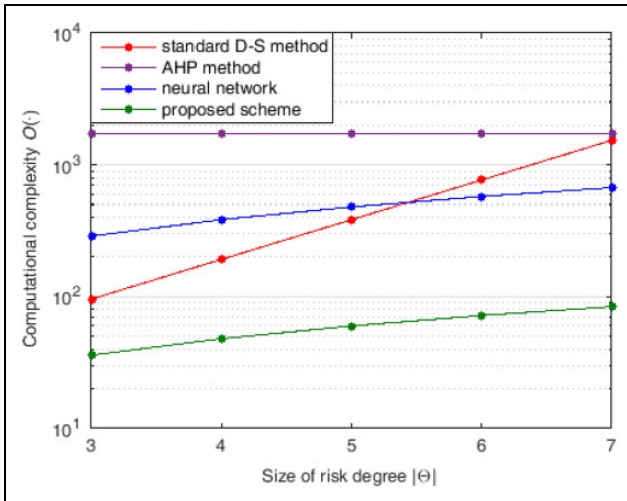


Figure 4. Computational complexity under different $|\theta|$.

some experts still affect the final decision. Further, the neural network gives relatively satisfactory result.

For the assessment efficiency, as a powerful criterion, the computational complexity is considered in depth. In Figure 3, we note that the larger the number of indicators χ , the higher the complexity O when the level of risks $|\theta|$ is fixed. Although it takes some time for the proposed assessment scheme to reassign the BPAs, the complexity keeps the smallest fluctuation against other methods. After the analysis, the complexity of the proposed scheme is almost $O(6\chi)$, whereas the standard D-S method has the complexity of $O(32\chi)$. For the AHP method, the eigenvalue of χ -order matrix is necessary when getting the coefficient of consistency ratio. Since the complexity reaches $O(\chi^3)$, it becomes more distinguished with the increasing χ . In the neural network (eight nodes in one hidden layer), the computational complexity approximates the product of the size of risk sets and the number of nodes in the hidden

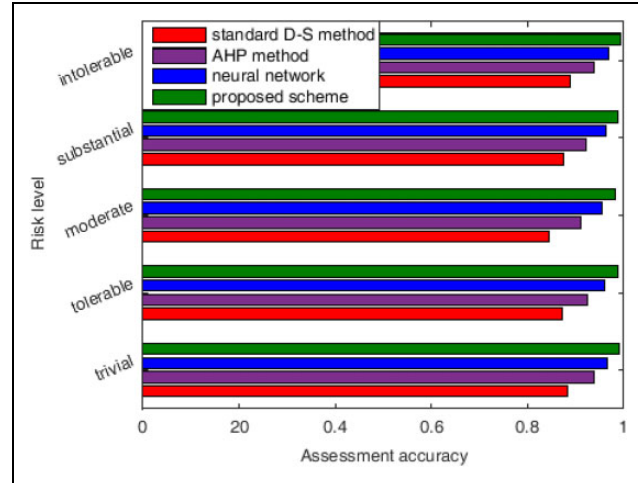


Figure 5. Averaged assessment accuracy.

layer, that is, $O(40\chi)$. On the other hand, we set the number of secondary indicators $\chi = 12$, and then obtain Figure 4. As seen, the computational complexity of standard D-S evidence theory and neural network is $O(12 \times 2^{|\theta|})$ and $O(96|\theta|)$, respectively. However, the AHP method has the maximum when χ is less than 7. The proposed scheme still keeps convergence when χ gradually increases, whose complexity is $O(12|\theta|)$.

Finally, Figure 5 presents the averaged assessment accuracy of risk levels under various trails. Note that the proposed scheme has the largest accuracy for each risk level with the innovative rule. Although the neural network and AHP method have the modest decision, there is some expert experience in the AHP method. Unfortunately, the standard D-S method fails to combine the uncertain and conflicting evidences, and then achieves unstable result.

Conclusion

This article develops an assessment scheme of VNR based on the fuzzy D-S evidence theory. We analyze the important indicators in the navigation engineering as an example. According to the fuzzy logic, the membership functions are derived to define five risk levels. In the enhanced D-S evidence framework, we further optimize the D-S evidence combination rule to deal with highly uncertain and conflicting evidences, which is more suitable to various applications. Finally, the numerical studies demonstrate that the intelligent decision can be achieved with the satisfactory performance for VNR assessment in the complex waters. As for the next research developments, we will further improve the assessment efficiency of the proposed scheme under the condition of insufficient indicators.


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