Effectiveness evaluation of underwater cluster based on improved RS-BP

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Abstract. In the modern underwater confrontation environment, efficient and accurate underwater cluster warfare effectiveness evaluation is essential. In order to solve the problem that the evaluation efficiency of the neural network evaluation model decreases with the expansion of the combat index system, the method of combining the rough set(RS) data reduction and BP neural network is used to construct the rough set reduction BP (RS-BP) neural network evaluation model to reduce the network input layer neuron quantity, optimize the initial weight learning of the neural network. The simulation results show that the convergence speed and evaluation accuracy of the RS-BP neural network model are improved.

1. Introduction
In modern naval warfare, relying solely on a single underwater unmanned aerial vehicle has been unable to meet the needs of complex combat missions, and the cooperation and synchronization between unmanned aerial vehicles has become an inevitable trend of development. Therefore, it promotes the construction and development of underwater cluster warfare [1]. Among them, how to evaluate its effectiveness more efficiently and accurately and give full play to its operational effectiveness is the current research focus.

At present, the widely used evaluation methods are analytic hierarchy process [2], cloud model evaluation method [3], gray correlation analysis method [4], etc., but these methods rely too much on expert experience and are easily affected by subjective factors, resulting in deviation in the evaluation results. And in the actual battlefield environment, the traditional evaluation methods lack the ability of adaptive adjustment and can not cope with the complex underwater combat environment. In recent years, artificial neural network has been widely used in the field of evaluation. Neural network evaluation is to update the evaluation model through test data, and finally obtain the effectiveness evaluation value, so as to effectively avoid over-reliance on expert opinions. Most of these studies improve the convergence speed and evaluation accuracy of neural network by combining other algorithms. In reference [5], genetic algorithm is introduced to improve the convergence speed and evaluation accuracy of the network. In reference [6], genetic algorithm is used to optimize the weight of RBF neural network globally, which ensures the objectivity of the evaluation results.

However, the above efficiency evaluation studies all assume that the index system is not redundant and lacks the analysis of the correlation degree of the index. The redundant index system will increase the number of neural network nodes, affect the weight of the index, and form a false index. Finally, it leads to the loss of fairness of the evaluation results and reduces the efficiency of the evaluation model. The neural network evaluation model lacks the ability to deal with missing data and is easy to fall into local optimization. For this reason, this paper selects and deletes the input vector of the neural network with the help of rough set, and avoids the neural network from falling into local optimization by introducing attribute reduction and data completion of rough set, and enables the neural network to
deal with uncertain data dynamically, so as to further improve the evaluation speed and ability of the network model.

2. Establishment of evaluation index system for underwater cluster warfare

Based on the analysis of several evaluation index systems of underwater cluster warfare, it is found that most of the research focuses on detection, accusation, attack and communication[7-9]. In this paper, starting with the target detection ability, information processing ability, command and decision-making ability and formation attack ability, and then combined with the environmental factors of underwater warfare, the underwater communication capability and system availability capability are introduced, and the underwater cluster combat index system shown in Table 1 is established.

Table 1. Index system of underwater cluster warfare.

| Secondary index                  | Tertiary indicators                                                                 |
|----------------------------------|-------------------------------------------------------------------------------------|
| Target detection capability      | Parameter measurement ability, target recognition ability, anti-interference ability, data integration ability |
| Information processing ability   | Intelligence acquisition ability, situation display ability, information fusion ability, data transmission ability |
| Accusation decision-making ability| Personnel reaction time, decision formation time, decision rationality, instruction issuing time |
| Formation attack ability         | Shell hit probability, target damage ability, missile single capacity, missile range, torpedo range |
| Underwater communication capability| Underwater acoustic channel diversity, communication delay, communication capacity, communication error rate |
| System availability              | Equipment availability, mission reliability                                         |

In the above operational index system, there are as many as 23 third-level indicators, so it is difficult to directly see the dependence and similar relationship between the indicators, so it is necessary to analyze their redundancy.

3. Attribute reduction based on rough set theory

In this paper, the evaluation index established in the previous section is reduced by means of the attribute reduction method of discernibility matrix.

3.1. Rough set principle

The formula of knowledge system in rough set is defined as: \( S=(U,R,V,f) \) among them, \( U \) is called domain; lettersrepr \( R \) esent the combination of multiple attributes. There's a relationship with \( R=C\cup D \), in which \( C \) is the set of conditional attributes, \( D \) is the set of decision attributes; \( V \) is the range of \( R \) ’s attribute values, \( f=U\times R\rightarrow V \) is a mapping that represents the value of an attribute in the domain. In any attribute subset \( B\subseteq R \), if the object \( x_i,x_j\in U,\forall k\in R \),And only if \( f(x_i,k)=f(x_j,k) \), then it is marked as an equivalent partition for \( x_i \) and \( x_j \). Write it down as \( U/ind(B) \), it is an equivalent partition for \( U \).

Rough set theory describes the equivalence of knowledge through information system, and redundancy can be deleted with the help of importance in knowledge base.
3.2. Discernibility matrix and its reduction rules

Paper is reduced by using significance as heuristic information. Firstly, the kernel attribute $P$ of the conditional attribute is obtained by discernibility matrix and the kernel attribute should be retained in the process of reduction. The discernibility matrix of knowledge system is:

$$M = \left[ a_{ij} \right]$$

$$a_{ij} = \begin{cases} \text{true} & a_i \in C, a_j \in C, a_i \neq a_j \cr \text{false} & \text{else} \end{cases}$$

$$M = \left[ \varnothing, D(x_i) = D(x_j) \right]$$

(1)

Among them, $i, j = 1, 2, \ldots, n$, the element $m_{ij}$ in the discernibility matrix is a set that can distinguish between a collection of all object attributes for object $x_i$ and $x_j$, its value is present as $a_i$. When $x_i$ and $x_j$ have the same decision attribute, the value of the element $m_{ij}$ is $\varnothing$ (empty set).

The set of single elements in the discernibility matrix is the core attribute of the knowledge system. Secondly, the importance of an attribute is defined as the frequency with which the attribute appears in $M(s)$, the definition for:

$$\text{imp}(C_i) = \frac{1}{m} \sum_{j=1}^{m} |C_i|$$

(2)

Where $C_i$ represents the $i$th conditional attribute in the set. $C_i$ represents the item in the matrix that contains the attribute. $m$ represents the number of conditional attributes in the collection.

After obtaining the attribute importance and core attribute $P$, the reduction starts from the core attribute set, adds conditional attributes to the core attribute set $P$ according to the attribute importance, and calculates the classification ability of the new set. When the classification ability of decision attributes remains unchanged after a new attribute is added to the core attribute $P$, the set is considered to be reduced, otherwise the attribute is considered to be redundant. The core attribute set is continuously added until all the attributes are traversed.

Finally, after the attribute importance $\text{imp}(C_i)$ is obtained, the index weight can be obtained by weighting, formula is as follows:

$$W_i = \frac{\text{imp}(C_i)}{\sum_{i=1}^{n} \text{imp}(C_i)}$$

(3)

4. Construction of rough set reduction neural network model for underwater cluster warfare

4.1. Reduction process of underwater cluster combat index system

The process of Index reduction taking formation attack Index as an example

Step 1: first encode the attributes of the indicators under the formation attack ability.

Step 2: invite 10 experts to issue a scoring opinion request form, and the experts will score according to the evaluation rules. Rough set needs discretized data when dealing with decision tables, but rough set theory lacks the processing of data discretization. This paper chooses the discretized reference table shown in Table 2 to discretize the scoring data, and taking into account the fuzziness of the evaluation problem, the qualitative evaluation is divided into five levels.

| Value | Assignment |
|-------|------------|
| $\geq 9$ | 5          |
| 8~8.9 | 4          |
| 7~7.9 | 3          |
| 6~6.9 | 2          |
| <6    | 1          |

Table 2. Data discretization reference table

Step 3: make up the missing data of the matrix with the help of formula (4), form the discrimination matrix through the discernment rule of formula (1), and find out the kernel attribute in the matrix.

Step 4: calculate and sort the importance of attributes with the help of formula (2), and then add conditional attributes to the core attribute set to determine whether the added set is still the simplest. The specific reduction rules are as follows:
If $U / \text{ind}(P \cup C) = U / \text{ind}(D)$, then the conditional attribute $C_i$ is a reducible attribute.

If $U / \text{ind}(P \cup C) \neq U / \text{ind}(D)$, then the conditional attribute $C_i$ is an unreducible attribute.

Step 5: calculate the weight of the attribute with the help of the formula (3).

4.2. Establishment of BP neural network optimization model for rough set reduction

The traditional BP neural network uses loss function to adjust the weight[11]. In practical application, when the number of network layers is too much, gradient dispersion will appear and fall into the local extremum. In this paper, BP neural network is optimized by rough set reduction, the model is shown in figure 1, and The steps are as follows:

Figure 1. Rough set reduction neural network flow chart

Setp1: Determines the network parameters such as hidden layer neurons of the initial BP neural network.

Setp2: Inputs the index data, carries on coding and discretization, and carries on the attribute reduction with the help of rough set to save the final index weight.

Setp3: Optimizes the structure of the neural network, and optimizes the number of neurons in the input layer and hidden layer of the BP neural network according to the reduced results.

Setp4: Takes the index weight obtained from the rough set reduction process as the best initial weight into the neural network evaluation model, and makes it train to reach the iterative termination condition set by the network training.

5. Analysis of simulation examples

5.1. System reduction verification

The reduction process takes the formation attack ability as an example. Firstly, the model discretizes the data of the expert scoring table. $abcde$ is used to represent the hit probability of conditional attribute shells, target damage capability, missile single capability, missile range and torpedo range respectively;
$D$ represents the decision attribute of formation attack capability, and the decision attribute table of formation attack capability is obtained as shown in Table 3.

|   | $a$ | $b$ | $c$ | $d$ | $e$ | $D$ |
|---|---|---|---|---|---|---|
| $P_1$ | 5 | 5 | 4 | 4 | 3 | 3 |
| $P_2$ | 2 | 1 | 3 | 4 | 1 | 3 |
| ... |
| $P_{10}$ | 3 | 4 | 3 | 1 | 2 | 1 |

Table 3. Formation attack ability decision attribute table

The resolution matrix is constructed by resolving matrix rules (Table 4), from which the kernel attribute {d} can be obtained. The attribute importance of the formation attack ability index is calculated, the calculated result is: \( \text{imp}(a)=4.715, \text{imp}(b)=3.750, \text{imp}(c)=4.325, \text{imp}(d)=5.313, \text{imp}(e)=3.210, \) and the sorting results are as follows: \( \text{imp}(d) > \text{imp}(a) > \text{imp}(c) > \text{imp}(b) > \text{imp}(e) \).

With the attribute importance as the heuristic information, the kernel attribute set \{d\} was successively added, and the reduction rule was used to determine whether an offer reduction was needed. The calculation was as follows:

\[
\begin{align*}
U / \text{ind}(D) &= \{\{P_1, P_2\}, \{P_3, P_4\}, \{P_5, P_6, P_7\}\} \\
U / \text{ind}(D) &\neq U / \text{ind}(d \cup a) \\
U / \text{ind}(D) &\neq U / \text{ind}(d \cup b) \\
U / \text{ind}(D) &\neq U / \text{ind}(d \cup c) \\
U / \text{ind}(D) &= U / \text{ind}(d \cup e)
\end{align*}
\]

Based on the analysis of the above calculations, we can see that the minimum reduction set of formation attack capability is \{a, b, c, d\}, With the help of formula (3), the weight of the index of formation attack ability is calculated,

The weights of the three-level index obtained under the formation attack ability are 0.221, 0.176, 0.202, 0.249, 0.152, respectively, indicating that the torpedo range has little effect on the effectiveness of the formation attack ability. this index is screened out in the process of reduction and the correctness of the reduction algorithm is verified.

5.2. Comparative analysis of performance results

The parameters of the neural network are set as shown in Table 5. The sample set of evaluation values shown in Table 6 is obtained by analyzing and collecting the experimental data in the literature [12-13]. 90 groups of scoring data were selected to bring into the effectiveness evaluation model for weight and threshold training.

| Sample | 1  | 2  | 3  | 4  | 5  | ... |
|--------|----|----|----|----|----|-----|
| E1     | 0.68 | 0.92 | 0.23 | 0.29 | 0.69 | ... |
| E2     | 0.85 | 0.56 | 0.54 | 0.72 | 0.85 | ... |
| E3     | 0.85 | 0.26 | 0.63 | 0.29 | 0.86 | ... |
| E4     | 0.27 | 0.39 | 0.96 | 0.99 | 0.59 | ... |
| E5     | 0.79 | 0.79 | 0.37 | 0.40 | 0.33 | ... |
| Value  | 0.63 | 0.56 | 0.58 | 0.56 | 0.73 | ... |

Table 6. Neural network parameter setting table

When constructing a neural network, taking formation attack capability as an example, the number of hidden layer nodes required is based on empirical formula and simulation iteration experiment. It can be seen that when it is equal to 11, it shows better evaluation results. while the improved rough set evaluation model only needs to construct 6 neurons after calculation and simulation. The number of neurons in the input layer dropped from 5 to 4. The data set was put into the 4-6-1 neural network.
evaluation model, and the convergence and efficiency evaluation of the evaluation algorithm before and after reduction were compared to analyze the practicability of the algorithm.

Figure 2. Error convergence of BP neural network

Figure 3. Error convergence of rough set reduction neural network

Figure 2 and Figure 3 shows that the BP neural network needs 1650 iterations to achieve the initial error accuracy. But the neural network of rough set reduction only needs 83 iterations to reach the initial setting accuracy. The convergence rate is significantly higher than before.

Figure 4. Comparison diagram of model evaluation efficiency value and actual efficiency value

Figure 5. Model evaluation error comparison diagram

In order to verify the accuracy of rough set reduction neural network evaluation model, this paper compares and analyzes the effectiveness evaluation and evaluation error of BP neural network, GA-BP neural network and rough set reduction BP neural network model. The comparison curve between the three groups of evaluated efficiency value and the actual efficiency value is shown in figure 4.

It can be seen from the diagram that compared with the other two evaluation models, the evaluation result of rough set reduction neural network is closer to the actual value and the fitting effect is better. In order to more intuitively explain the difference between the output value and the actual value of the three evaluation models, the evaluation errors of the three models are calculated, as shown in figure 5.

From the diagram, we can see that the evaluation error of rough set reduction neural network evaluation model is relatively stable and close to 0, which shows that the evaluation error accuracy of rough set reduction neural network is higher.
6. Conclusion
In this paper, the rough set attribute reduction method is used to complete the reduction of the input vector of the neural network, which removes the redundant attributes in the set and reduces the number of neurons in the data dimension and the hidden layer of the neural network, and improves the evaluation efficiency. At the same time, in the weight learning of the neural network, the attribute weights obtained in the reduction are studied as the initial weights, and the weights are adjusted in the optimal area when the weights are updated, so as to prevent the neural network from falling into the local optimal. By comparing and analyzing the evaluation value and error accuracy of RS-BP neural network evaluation model, traditional BP neural network evaluation model and GA-BP neural network evaluation model, it is concluded that RS-BP neural network has the best performance in evaluation accuracy and error, and the convergence speed is faster, which finally verifies the advantages of the improved RS-BP neural network effectiveness evaluation model.

Acknowledgments
Supported by the National Natural Science Foundation of China (NO: 61540024)

References
[1] Zhang W, Wang N.X, Wei S.L, Du X, Yan Z.P. (2020) Summary of the development status and key technologies of UAV cluster [J]. Journal of Harbin Engineering University, (2020): 289-297.
[2] Zhu C.Z., Ji P.C, Li J, Ni Z. (2020) Quantitative Evaluation method of warship operational effectiveness based on Analytic hierarchy process. Chinese Institute of Command and Control. Proceedings of the 8th China Command and Control Congress [C].
[3] Liu B.Q, Hu J.B, Li J. (2020) Aviation equipment maintenance support capability evaluation based on cloud model [J]. Firepower and Command and Control, 45 (03): 138-143.
[4] Huang M.D, Xia T.B, Zhang H, Song F, Fan L.Y. (2020) Study on the effectiveness Evaluation of National quality Infrastructure on the quality of Export products [J/OL]. Industrial Engineering and Management.
[5] Zhu M, Lu Q, Ding Y.M. (2020) Operational effectiveness Evaluation of underwater Cluster based on GA-Elman Neural Network [J]. Fire Control & Command Control(07): 115-119,125.
[6] Du X.L, Zhou M, Lu Y.N, Qiu S.M. (2020) Effectiveness Evaluation of equipment support system based on optimized RBF Neural Network [J/OL]. Computer engineering 1-18.
[7] Wang Y, Guo X.W. (2019) Research on the Application of Unmanned system Cluster in Maritime Operations [J]. Warship Electronic Engineering, 39 (12): 21-25
[8] Yan Z.P, Liu X.L. (2019) Research status and development trend of multi-UUV coordinated control technology [J]. Journal of Unmanned underwater Systems, 27 (03): 226-231.
[9] He L.W. (2018) Research on Multi-UUV Target search and tracking method for Island and Reef Surveillance [D]. Harbin University of Engineering.
[10] Lu X.H, Chen S.Q, Wu J.P. (2003) Heuristic attribute reduction method based on discernibility matrix and its application [J]. Computer Engineering, (01): 56-59.
[11] Deng X.Z, Ye B. (2019) Effectiveness Evaluation of Airborne embedded training system based on immune BP Network [J]. Computer Technology and Development, 29 (12): 173-177.
[12] Cao F.F, Liu W.D, Li J.L.( 2011) Multi-UUV cooperative combat effectiveness evaluation based on underwater network [J]. Computer Measurement and Control, Magi 19 (06): 1397-1399 1402.
[13] Xu H, Kang F.J, Li D.(2015) Operational effectiveness evaluation method of anti-torpedo weapon system [J]. Computer Engineering and applications, 51 (02): 265-270.