Integrated Power System Health Assessment of Large-Scale Unmanned Surface Ships Based on Convolutional Neural Network Algorithm

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Abstract. These paper studies the large unmanned ship of the most advanced electric propulsion method. Its integrated power system is complex in structure with many equipment and often performs long-range operations. The key factor of the large unmanned ship is the integrated power system of healthy operation. This paper analyzes the parameters affecting the health of the system from three aspects: the system parameters, the unmanned ship's navigation state parameters, and the environmental parameters and designs a kind of unmanned ship integrated power system health based on Evaluation algorithm of convolutional neural network with high accuracy. In this paper, the feasibility and superiority of convolution neural network algorithm are verified through the comparative simulation analysis of BP neural network and deep belief network.

1. Introduction
Large-scale unmanned ships mainly refer to an unmanned ship of displacement of more than one hundred tons. The main propulsion methods adopt the most advanced all-electric propulsion at present. The integrated power system is the core subsystem [1], which is composed of electric system and power system with complex structure and many equipment. It is the general name of the network formed by the production, distribution and use of electrical energy in large unmanned ships and the device for converting electrical energy into kinetic energy [2]. Its health status directly affects the operational status of the entire unmanned ship. Therefore, the comprehensive power system needs to be evaluated for health operations, and its evaluation results represent whether unmanned ships can safely navigate operations.

The health assessment algorithm is the core and main research work of the health assessment. The result of the algorithm directly determines whether the integrated power system needs to be repaired, and then affects the unmanned ship's navigation operation plan and safety. HG Melhem proposed the method of weighting according to the degree of importance of the parameters and applied weak α segmentation and fuzzy for health product assessment, and successfully evaluated the health status of the bridge [3]. Zhang Liang et al. used the rough set method to determine the health feature sample reductions and weights, and then assessed the health status of the equipment using the weighted nuclear distance [10]. In addition, Dai Jing et al. proposed the application of a structured Bayesian network method in health assessment [5]. However, the algorithms used have some problems such as slow
convergence rate, falling into local optimal solution, and assessing the accuracy rate, which causes
problems for practical applications.

Based on the actual project requirements above, this paper uses convolutional neural network
algorithm to build an integrated power system health assessment model for unmanned ships. After
training and verification of the model, the health assessment of the integrated power system is finally
performed for simulation analysis.

2. Selection of evaluation feature parameters

Because of the complexity of large-scale unmanned boat operations and be interfered by different factors.
Therefore, we need to measure the degree of influence of various factors on the integrated power system
[6] to select suitable parameters as the characteristic parameters of the system health assessment [4]. As
shown in Table 1.

| Table 1. Characteristics of Statistical Information of Unmanned Ships’ Navigation Parameters |
|-----------------------------------------------|------|------|------|
| Name                           | Unit | Min  | Max  | Mean |
| System voltage (XY)        | V    | 950  | 1155 | 1031 |
| Frequency (XP)             | Hz   | 49.85| 50.32| 50.01|
| Power (XL)                  | kW   | 1266 | 1709 | 1589 |
| Inverter temperature (BW) | ℃    | 23.2 | 51.3 | 32.3 |
| Temperature difference (SW)| ℃    | 55.6 | 89.2 | 68.3 |
| Motor speed (DW)           | r/min| 265  | 498  | 375  |
| Winding end temperature (FW)| ℃   | 13.3 | 106.5| 52.2 |
| Diesel engine oil pressure (CY)| kPa | 72   | 192  | 161  |
| Rectifier temperature (ZW) | ℃    | 35.6 | 75.2 | 53.2 |

2.1. Data processing steps

Dispose of 1100 data sets of a large unmanned ship as follows:

1) The normalization process is performed first. $x_i$ For the test data, the standard value is $x_m$, the
upper and lower limits of the value are $\bar{x}$, $\bar{x}$ and the deviation of the test data from the standard data is
that $\Delta x = |x_i - x_m|$, based on the maximum value of the upper and lower limits $\delta = |\bar{x} - x_m|$, $\delta = |ar{x} - x_m|$, the maximum allowable error is obtained as Normalized value:

$$
\lambda_i = \begin{cases} 
\frac{\delta - \Delta x}{\delta} & x_m \leq x_i \leq \bar{x} \\
\frac{\bar{x} - \Delta x}{\delta} & x_i \leq x_m 
\end{cases}
$$

2) It is discretized and divided into three categories: fault (0~0.35), sub-health (0.35~0.8), and health
(0.8~1), which are replaced by numbers 3, 2, and 1, respectively. According to this rule, discretized data
is obtained.

3) Then, the rough set attribute dynamic reduction algorithm [7-8] is used to perform the reduction
calculation, so that, $U_k$, k=1, 2, 3, 4… N, for the domain subset, the attribute reduction set corresponding
to each universe can be calculated by the dynamic reduction of the rough set $RED_k$. $a_j, j=1, 2, 3,..M$ in
the $RED_k$ Medium weight is:

$$
W_{kj} = \begin{cases} 
\frac{\text{sig}_{k}(a_j,RED_k,D,\beta)}{\sum_{j=1}^{M}\text{sig}_{k}(a_j,RED_k,D,\beta)} & a_j \in RED_k \\
0 & a_j \notin RED_k
\end{cases}
$$
2.2. Data processing results

The 1100 data sets of unmanned boats were grouped and grouped into a sample set of 120 data, which was divided into 15 groups. After the 9 sets of data are calculated by reduction, the cumulative evaluation results of the weights are shown in Table 2.

| Number | XY   | XP   | XL   | BW   | SW   | DW   | FW   | CY   | ZW   |
|--------|------|------|------|------|------|------|------|------|------|
| 1      | 0.135| 0.028| 0.121| 0.015| 0.025| 0.099| 0.032| 0.051| 0.132|
| 2      | 0.125| 0.027| 0.121| 0.017| 0.029| 0.109| 0.027| 0.045| 0.130|
| 3      | 0.119| 0.020| 0.113| 0.014| 0.035| 0.115| 0.038| 0.044| 0.130|
| 4      | 0.121| 0.017| 0.115| 0.014| 0.055| 0.113| 0.041| 0.047| 0.130|
| 5      | 0.124| n/a  | 0.116| 0.013| 0.045| 0.118| 0.042| 0.052| 0.130|
| 6      | 0.124| n/a  | 0.116| 0.013| 0.045| 0.121| 0.047| 0.065| 0.130|
| 7      | 0.135| n/a  | 0.118| n/a  | 0.045| 0.119| 0.055| 0.069| 0.130|
| 8      | 0.141| n/a  | 0.120| n/a  | 0.045| 0.119| 0.54  | 0.069| 0.130|
| 9      | 0.148| n/a  | 0.121| n/a  | 0.046| 0.123| 0.52  | 0.071| 0.130|
| 10     | 0.178| n/a  | 0.125| n/a  | 0.135| n/a  | 0.073 | 0.130|

From the above table, the initial evaluation parameters are analyzed, and the main parameters affecting the health of the system are finally determined as: system voltage (XY), power (XL), motor rotation speed (DW), rectifier device temperature (ZW).

3. System health assessment model

Convolutional neural network is an algorithm mainly used for image recognition. When the convolutional neural network recognizes the signal of the integrated power system, it needs to convert the signal into image information first, which is the input of the convolutional neural network model [9]. Considering that there are four main influence parameters obtained from the rough set theory, the convolutional neural network model with different inputs does not have universality. Therefore, this paper will establish four assessment models based on input parameters and conduct training and testing respectively.

3.1. Model training process

1) Initialize the model's weight matrix and offset parameters, and the initial value can be random;
2) Assuming that the number of samples is k, select the sample \(X_k\) and input it into the model for training to get the output result \(O_k\);
3) Calculate the error between the actual output vector \(Y_k\) and the ideal output vector \(O_k\), expressed as a squared difference. The error formula is:

\[
E_k = \frac{1}{2} \sum_{k=1}^{R} (Y_k - O_k)^2
\]

4) The error obtained in the previous step is propagated back to back in layers, and then the gradient of the error cost function to the parameter is obtained by the stochastic gradient descent method. Then the weight parameter is updated, and the parameter updating formula is:

\[
W_k(t + 1) = W_k(t) - \alpha \frac{\partial E_k}{\partial W_k(t)}
\]
5) T Express the number of iterations, \( \alpha \) represent the learning rate, and range from 0 to 1.

6) Input the remaining training samples into the network one by one, and follow the steps 2) to 4). Train all samples, indicating that one iteration is completed;

7) According to the number of iterations set by the user or the recognition accuracy as the conditions for training completion, when the conditions are met, the model training is completed.

3.2. Analysis of model training results

Training analysis: According to the set initial parameters, the model is trained, and their influence on the model recognition rate is analyzed from the training times, the structural parameters of the model, and the number of batches. In the parameter processing, 1000 samples were created for each kind of signal, 700 of them were randomly selected as training data, and the rest were used as test data. The sampling width of the first layer of this study model is set to 3*3, the sampling width of the second layer is set to 2*2, and the sampling method is the maximum sampling method. Figure 1 shows the result between the evaluation accuracy and the number of iterations.

![Figure 1. Model training results](image)

4. Simulation verification

In order to make the model research algorithm comparative, for the image depth belief network and convolutional neural network, the four kinds of input signals are modeled separately, and the average value of the four model evaluation results is used as the performance evaluation index of the algorithm. For the BP neural network, the signal in 4 is composed of a vector as the input of the model show as Figure2.
Then analyze the average evaluation accuracy and evaluation time of the three algorithms, and calculate the average evaluation time and evaluation accuracy of the above 15 experiments, as shown in Table 1.3.

| Algorithm category | Average assessment Accuracy (%) | Average training time |
|--------------------|---------------------------------|-----------------------|
| DBN                | 98.07                           | 3025.8                |
| BP                 | 91.77                           | 5364.7                |
| CNN                | 98.77                           | 170.9                 |

From Table 3, it can be analyzed that the average health status assessment accuracy of the three algorithms exceeds 91%, and the average accuracy of the BP neural network is at least 6.8% lower than the other two algorithms, and its evaluation time is also far greater than them, this shows that the shallow neural network's assessment ability is far less than the deep learning algorithm. The evaluation accuracy of convolutional neural network and deep belief network is not much different, but the evaluation time of convolutional neural network is only 170.9 seconds, accounting for 3.2% of BP neural network and accounting for 5.6% of deep belief network. This shows that the convolutional neural network algorithm has better performance in health assessment.

5. Conclusion
Based on the extracted feature parameters, this paper proposes a convolutional neural network method to evaluate the health status of unmanned ship integrated power system. Firstly, according to the characteristics of the system, system health assessment process has been formulated. Secondly, through training, the parameters of the model network established based on different characteristic parameters are determined. Thirdly, the health evaluation ability of the model is verified through tests. The comparison between the models is performed to verify the correctness of the selection of the characteristic parameters. Finally, compared with other methods of deep belief network and BP neural network to verify the feasibility of convolutional neural network in the field of health assessment. It was
found that convolutional neural network has the highest accuracy in the health assessment and less training time than the other two algorithms.

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