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Research on Big Data Intelligent System for Fault Diagnosis of Computer Aided Ship Power System

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Abstract: This paper aims to build a new fault diagnosis system based on big data and artificial intelligence technology. This study first expounds the application value and prospect of big data technology and intelligent algorithm in the fault diagnosis of ship power system, and realizes the effective integration and mining of massive, multi-source and heterogeneous ship power system operation data through in-depth analysis of the characteristics of ship power system operation data. Secondly, in view of the nonlinear and time-varying characteristics of ship power system faults, this study designs and implements a fault diagnosis model that integrates intelligent algorithms such as machine learning and deep learning. The model can automatically extract key fault features, realize early warning and accurate identification of potential faults, and improve the accuracy and response speed of fault diagnosis through continuous learning and optimization. Finally, this study applies the big data intelligent system for fault diagnosis of computer-aided ship power system to a practical case to verify its effectiveness and practicability in improving fault diagnosis efficiency, reducing maintenance costs, and ensuring navigation safety. The research results have important theoretical significance and practical value for improving the level of ship operation and maintenance management and ensuring the stable operation of ship power system.

Keywords: Computer Aided; Marine Power System; Fault Diagnosis; Big Data Intelligent System.

1. Introduction

With the rapid development of modern ship technology, the structure of ship power system is becoming more and more complex, which poses an unprecedented challenge to the accuracy and real-time fault diagnosis. Based on this frontier problem, this paper is committed to developing a new fault diagnosis system that deeply integrates big data technology and artificial intelligence algorithm, in order to solve the problems existing in the fault diagnosis of the current ship power system, so as to improve the safety and economy of ship operation. Firstly, the paper discusses the application value and broad prospect of big data technology and intelligent algorithm in fault diagnosis of ship power system in detail. In the face of the massive, multi-source and heterogeneous operation data generated by the ship power system, we use the deep data analysis method to reveal the operation rules and fault characteristics hidden behind the huge data. Through the use of advanced big data processing technologies, such as streaming computing and distributed storage technology, we effectively integrate, process and deeply dig large-scale complex data, thereby solving the problems of low time efficiency and resource waste that may occur in the face of massive data by traditional methods. On this basis, this research pays special attention to the nonlinear and time-varying characteristics of the ship power system, and then carefully designs and successfully applies a fault diagnosis model integrating multiple intelligent algorithms such as machine learning and deep learning. The model has strong self-learning and optimization ability, and can automatically extract key fault characteristic parameters in real-time monitoring, so as to give early warning at the early stage of fault occurrence, and accurately identify various potential fault types. Through continuous iterative training and optimization, the model significantly improves the accuracy and response speed of fault diagnosis, and effectively overcomes the limitations of traditional fault diagnosis methods in dealing with complex and dynamically changing systems. Finally, in order to verify the practicability and effectiveness of the above big data intelligent fault diagnosis system, this study applied it to several fault diagnosis examples of ship power system. The results show that the system can not only greatly improve the fault diagnosis efficiency and reduce the unnecessary maintenance cost caused by misdiagnosis or delay, but also play a vital role in ensuring navigation safety. This research result not only has great value for the innovative development of China's shipbuilding industry, but also provides a new idea and solution for the progress of fault diagnosis technology in the global shipbuilding industry.

In general, through in-depth exploration and practical application of big data intelligent technology, this paper effectively verifies its important role in improving the fault prediction accuracy of ship power system and reducing the fault detection time. This research result not only has profound theoretical guiding significance, but also has significant practical value for optimizing the efficiency of ship operation and maintenance management and ensuring the robust and efficient operation of ship power system. In the future research, we will continue to deepen and improve the ship power system fault diagnosis system based on big data intelligence, in order to adapt to a wider range of engineering application scenarios, and actively promote the continuous evolution and development of smart Marine equipment technology.

2. Related Work

Fault diagnosis technology is the core means to ensure the safe operation of equipment, involving four aspects: signal detection, feature extraction, state recognition and prediction decision [1-2]. Many research teams at home and abroad have carried out in-depth research in this field. For example, Z. Eng et al. used oil monitoring technology to study the wear particle characteristics of motor driven turbine box, and combined with vibration monitoring technology to improve the fault diagnosis accuracy [3]. Anand Prabhakaran et al. conducted long-term monitoring of the lubricating oil of the turbine generator set and used various analysis methods to extract pollutant information to study the faults caused by oil pollution [4]. Liu Tao et al. analyzed diesel engine oil samples with the help of M-type atomic spectrum analyzer and revealed the element source and its relationship with diesel engine condition monitoring and wear diagnosis [5]. The Reliability Engineering Research Center of Wuhan University of Technology has accumulated rich theoretical and practical experience in oil monitoring of Marine power system, and has monitored abrasive content, viscosity, water content and other indicators by installing online monitoring systems [6]. In addition, X. Piyan et al. used online ferrospectrometer to monitor wear particles in ship power system in real time, and effectively reflected equipment wear status through IPCA index [7]. Sheng Chenxing et al. deployed a computer-aided monitoring system for pollution degree on the dredger to realize real-time hierarchical alarm monitoring of the oil pollution degree of the ship's hydraulic system [8]. Li. B et al. conducted time-frequency domain analysis of motor bearing vibration signals, and used neural networks for bearing fault diagnosis [9]. Zhixiong Li et al. comprehensively used vibration analysis and wear particle analysis, combined with ICA-R algorithm to achieve non-destructive diagnosis of ship main engine wear fault. Professors Yang Jianguo and Zhou Yichen used the surface vibration signal of diesel engine to judge the wear fault state [10]. In summary, these studies have significantly improved the fault prediction accuracy and diagnosis efficiency of all kinds of machinery and equipment, especially ship power systems, through diversified monitoring means and intelligent diagnosis methods.

3. MODEL

3.1. BP Neural Network Model

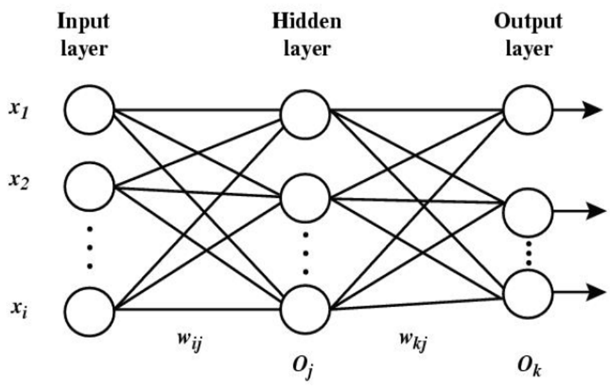

Figure 1. BP neural network model

Figure 1 illustrates the Backpropagation Neural Network (BPNN), which is a prevalent artificial neural network model employed extensively for training multi-layer feedforward architectures. This model comprises three key parts: an input layer, one or more hidden layers, and an output layer. Each neuron within these layers is interconnected through weighted connections, and non-linear activation functions are utilized to transform the signals. During the training phase, the BPNN operates by backpropagating errors from the final output layer towards the input layer. It iteratively adjusts the weights and biases layer by layer, based on the discrepancies between the predicted and target outputs. This iterative process aims to gradually reduce the cumulative error across the entire network, thereby enhancing its accuracy and performance.

Through repeated iterative training, BP neural network can learn the complex mapping relationship between input and output, and is suitable for various data processing tasks such as classification, regression, prediction, etc., showing strong generalization ability and practicability in pattern recognition, fault diagnosis, machine learning and other fields. Input the hidden layer of BP neural network in the fault diagnosis system to output calculation formula 1:

$$h(t) = y_t\left(\frac{\sum_{i=1}^{n}\delta_i x_i - a_i}{b_i}\right) \tag{1}$$

Wherea_i and b_i b_i are the weights of the input layer and the hidden layer respectively. $F_n(t)$ is the expected output, and $F_0(t)$is the calculated output of BP neural network. Error calculation formula 2 for fault diagnosis and prediction is as follows:

$$e = \sum_{i=1}^{n} F_n(t) - F_0(t) \tag{2}$$

3.2. Genetic Algorithm (GA)

As shown in Figure 2, Genetic algorithm (GA) is a global optimization search algorithm that simulates the biological evolution mechanism in nature. Through the selection, crossover (hybridization) and variation of individuals in the population (encoded as the solution space representation of chromosomes), it gradually iterates to produce a new generation of populations, so as to seek the optimal solution. Each person can be seen as a prospective answer to an issue, and the merit of this solution is assessed using the objective function. The greater the fitness score, the higher the quality of the solution being presented. In other words, every individual in the context of optimization or problem-solving is akin to a possible solution, and the effectiveness of that solution is gauged through the application of an objective function. A higher fitness value implies that the solution is of superior quality. Genetic algorithm is especially good at dealing with high-dimensional, non-linear, multi-modal optimization problems, and can maintain diversity in the solution process and effectively avoid the local optimal trap, and is widely used in engineering design, scheduling optimization, machine learning, fault diagnosis and many other fields. There are two core steps:

First, at the individual representation level, we established a encoding form in which each individual was abstracting into a sequence of feature vectors containing attribute variables (x_1 to x_n) corresponding to a set of candidate features to be considered in the ship power system fault diagnosis.

Secondly, a fitness function model is constructed, labeled F. In this model, the accuracy parameter reflects the actual recognition accuracy obtained by performing fault classification task on BP neural network based on a given feature set. complexity quantifies the dimensional size or computational complexity of the feature set itself. The core function of this fitness function is to comprehensively evaluate the efficiency and quality of each feature set.

$$F = f(classification, accuracy, complexity) \quad (3)$$

After that, the genetic algorithm is used to solve the problem as follows: First, the population is initialized, and a series of feature combinations are randomly constructed to form an initial individual set (population). The second step is fitness evaluation. For each individual associated feature set, the BP neural network is used to conduct fault diagnosis experiments, so as to calculate the corresponding fitness value. The third step is to select excellent individuals to enter the next generation population according to the fitness value. The fourth step is crossover, that is, perform crossover operations to exchange some features of the two parent individuals and generate new child individuals. The fifth step of variation is to mutate some characteristics of the offspring individuals according to a certain probability to increase the diversity of the population. The sixth step involves cycling through the process, meaning that the previous actions are reiterated until either the pre-established limit of iterations has been achieved or until a satisfactory ensemble of fault diagnosis features has been successfully identified.

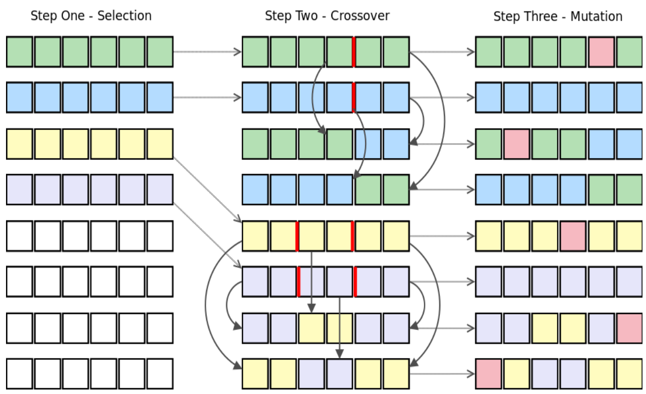

Figure 2. Genetic Algorithm (GA)

3.3. BP-GA Model

In this paper, the advantages of BP neural network and genetic algorithm are cleverly integrated, and a new BP-GA model is proposed. The process is shown in Figure 3.

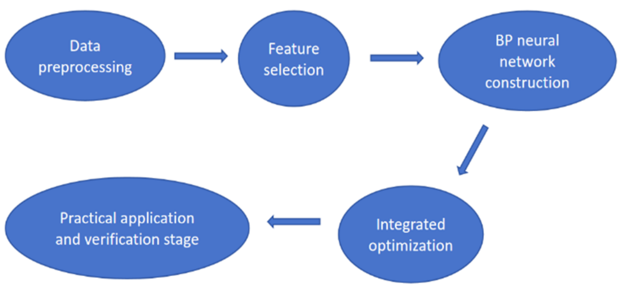

Figure 3. BP-GA MODEL

Data pre-processing stage: First, collect and integrate multiple, heterogeneous and massive operation data of the ship power system, including but not limited to sensor monitoring data, equipment status parameters, fault records, etc. Through data cleaning, normalization and other preprocessing methods, the original data is transformed into a form suitable for model input.

Feature selection stage: genetic algorithm is used for feature selection and optimization. According to the requirements of fault diagnosis, the fitness function is designed, and the feature subset that is most influential to fault diagnosis is screened through genetic operations such as population initialization, selection, crossover and mutation, so as to reduce the model complexity and improve the diagnosis efficiency.

BP neural network construction stage: Using the optimized feature set to build the BP neural network model. The model typically consists of an input layer (corresponding to selected feature variables), a hidden layer (performing nonlinear transformations and feature learning), and an output layer (giving probabilistic predictions of fault types). The weight and threshold of the network are trained by the backpropagation algorithm, so that the model can accurately fit the fault data, and realize the identification and prediction of all kinds of faults in the ship power system.

During the stage of integration and refinement, we merge the genetically optimized feature set with a Backpropagation Neural Network (BPNN) to establish a holistic model. The BPNN's preliminary parameter configurations and architectural design undergo continuous, iterative refinement via the genetic algorithm. This rigorous optimization process ensures that when confronted with the intricate and variable data scenarios in a ship's power system, our entire fault diagnostic system can execute fault identification and early warning tasks with significantly heightened precision and expedited speed.

In the practical application and verification stage, we will deploy the constructed composite model in the real fault diagnosis environment of the ship power system to monitor the running state of the ship power system in real time. The model will receive and analyze the obtained data information in real time, and then generate fault prediction results. By comparing the actual fault conditions, we constantly adjust and improve the model performance. This process aims to verify the effectiveness and practicability of the model in practical application scenarios such as enhancing the accuracy of fault diagnosis, reducing maintenance expenditure, and ensuring navigation safety.

4. Experiment

4.1. Data Set

This research draws upon an experimental dataset sourced from a ship's power system operating in genuine environmental conditions, encompassing a broad spectrum of data categories and origins. The dataset includes, among others, live operational status data, alarm details, maintenance logs, and historical fault cases emanating from core propulsion machinery such as main engines, auxiliary engines, and their respective control systems, alongside electrical apparatuses, hydraulic systems, and associated sensor networks. These data sets are large in scale, diverse in structure and dynamically updated, reflecting the complexity and nonlinear characteristics of ship power system operation. Specifically, the experimental data set contains a large number of continuous real-time monitoring data, such as temperature, pressure, speed, vibration, noise and other key parameters, as well as various equipment working mode, load status, energy consumption indicators and other information. At the same time, there are some discrete data, such as equipment start and stop state, fault alarm signal. All of this data is pre-processed and standardized to facilitate effective integration and deep mining using big data processing techniques. In the stage of building fault diagnosis model, the research team carefully selected representative fault sample data based on actual fault cases for training and verifying the intelligent fault diagnosis model that integrates machine learning and deep learning algorithms. Through the model learning and iterative optimization of massive data, the automatic feature extraction and accurate identification of various typical faults of the ship power system are realized, so as to achieve the purpose of early warning and rapid fault location. Finally, in a series of practical application cases, the superior performance of the big data intelligent fault diagnosis system in improving diagnosis efficiency, reducing cost and ensuring navigation safety is confirmed.

4.2. Evaluation Index

Diagnostic accuracy: This is the most basic and important evaluation index, which is used to measure the accuracy of the model to identify the fault types of the ship power system. The classification accuracy of the model on the test set can be calculated by cross-validation and other methods.

Recall rate: It is how many truly relevant instances the model or system can find, that is, the proportion of all samples that are actually positive that the model successfully identifies. In areas such as fault diagnosis, the high recall rate means that the model can find more actual problems and reduce the risk of missed diagnosis or omission of important events. The evaluation formula is shown in Publicity 4:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Precision: For multi-class fault diagnosis problems, recall rate and precision rate can be used to evaluate the model's ability to detect various types of faults and avoid false positives and missed positives. The calculation is shown in Publication 5:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

F1 score: The F1 score acts as a unifying metric that blends the recall rate and precision rate into a single measure, thereby providing a comprehensive reflection of a model's performance in both accuracy and completeness of detection. It calculates the harmonic mean of precision and recall values. When examining the experimental findings, this metric offers valuable insights.

4.3. Experimental Result

Table 1. Comparison of experimental results

MODEL	Recall	Precision	F1
BP	98.70%	96.14%	97.42%
GA	97.65%	95.67%	96.66%
BP-GA	99.23%	98.34%	98.79%

According to the experimental results in Table 1, we can compare and analyze the performance of three different models, BP model, GA model and their integrated model (BP-GA), in the fault diagnosis of ship power system:

Recall: This measure measures the model's ability to correctly identify failure samples. The data show that the recall rate of the BP neural network model is 98.70%, the genetic algorithm model is 97.65%, and the BP-GA hybrid model reaches the highest 99.23%. This means that BP-GA hybrid model has the best performance in identifying fault samples and can minimize the possibility of missed faults.

Precision: This indicator reflects how many of the samples predicted by the model to be failures are actually failures. The accuracy of the BP neural network model is 96.14%, the genetic algorithm model is 95.67%, and the BP-GA hybrid model is as high as 98.34%. This shows that the BP-GA hybrid model has a significant improvement in avoiding false positives compared to the other two models, reducing the risk of misidentifying normal samples as faulty samples.

F1 score (F1): The F1 score serves as a harmonized metric that equally weighs precision and recall, thereby offering a holistic evaluation of a model's effectiveness. With the BP (Backpropagation) model achieving an F1 score of 97.42%, the Genetic Algorithm model attaining 96.66%, and the BP-GA hybrid model topping the chart at 98.79%, it becomes evident that the integrated model resulting from the fusion of Backpropagation Neural Network with Genetic Algorithm outperforms standalone models in terms of overall efficiency. This higher F1 score of 98.79% for the BP-GA hybrid underscores its superiority in comprehensive performance.

In summary, in the task of fault diagnosis of ship power system, the BP-GA hybrid model combined with BP neural network and genetic algorithm has achieved the best performance in the three key evaluation indicators of recall rate, accuracy rate and F1 score, showing higher diagnostic accuracy and stability. It provides a more powerful and reliable solution for intelligent fault diagnosis of Marine power system.

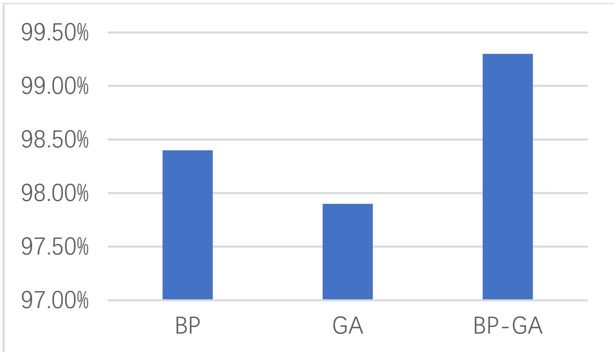

Figure 4. Comparison of diagnostic accuracy

As shown in Figure 4, when evaluating the performance of computer-aided models for fault diagnosis of ship power system, we compared the performance of three models: BP neural network model (BP), genetic algorithm model (GA), and BP-GA hybrid model combined with them in terms of diagnostic Accuracy. The data show that the diagnosis accuracy of BP neural network model is 98.40%, which indicates that the model has high recognition accuracy when processing fault diagnosis tasks independently, and can accurately identify most of the ship power system faults. The diagnosis accuracy of the genetic algorithm model is 97.90%, which is slightly lower than the BP neural network model, but it also shows strong fault diagnosis ability, and can effectively judge and predict the fault state of the ship power system to a certain extent. However, when BP neural network is combined with genetic algorithm to construct a BP-GA hybrid model, its diagnostic accuracy jumps to 99.30%. This significant improvement means that after integrating the advantages of the two algorithms, the BP-GA hybrid model can identify and judge the fault phenomena of the ship power system more accurately, thus greatly improving the accuracy and reliability of fault diagnosis. In summary, although the BP neural network model and the genetic algorithm model show good performance in the fault diagnosis of the ship power system, the BP-GA hybrid model, by virtue of its advantages of integrating the two advanced algorithms, effectively improves the diagnosis accuracy rate and reflects stronger fault identification capability, providing a more ideal solution for the intelligent fault diagnosis of the ship power system.

5. Conclusion

This research successfully developed a ship power system fault diagnosis system based on big data and artificial intelligence technology, made full use of big data technology to integrate and mine complex multi-source ship operation data, combined with machine learning and deep learning algorithms to solve nonlinear and time-varying fault diagnosis problems. The constructed intelligent model can automatically extract key fault features and realize early warning and accurate identification, which significantly improves the diagnosis accuracy and response speed. The practical application shows that the system can effectively improve the fault diagnosis efficiency, save maintenance cost and strengthen navigation safety. This achievement not only provides a revolutionary intelligent fault diagnosis solution for China's ship industry, but also has a wide range of application prospects in the world, and effectively promotes the progress and development of intelligent Marine equipment technology.

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