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COMPUTER SIMULATION AND SIMULATION OF MECHANICAL AND ELECTRICAL EQUIPMENT BASED ON ARTIFICIAL INTELLIGENCE ALGORITHMS

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Abstract. The computer in mechanical and electrical equipment can now detect equipment faults through simulation thanks to the advancement of artificial intelligence (AI) technology, which makes it convenient to monitor mechanical and electrical equipment. This paper begins with a quick introduction to Agent and the Agent system, explains how Agent is applied in the current context, then analyzes the hierarchical fault diagnostic model, identifies its flaws, and suggests improvement techniques. To increase the model's accuracy and speed of operation, the contract net model and D-S (Dempster-Shafer) evidence theory are then incorporated. Finally, simulation experiments are used to confirm the accuracy and consistency of this model. According to the experimental findings, this optimization model runs at a pace that is noticeably faster than that of other models when subjected to the same workload, demonstrating the model's efficacy. Models 1, 2, and 3 are put side by side to demonstrate how clearly multi-task processing may cut down on the model's running time. In the second experiment, samples of mechanical and electrical equipment defect data are taken from two groups. The results of the comparative experiments demonstrate that the optimized model in this work can be reliable up to a maximum of 0.91 and a minimum of 0.63. It is demonstrated that the model in this work is rational by the fact that among the four types of fault prediction, the optimized model's reliability is significantly greater than the traditional model's. The research described in this publication therefore has some reference value for computer simulation of electromechanical equipment.

Key words: Artificial intelligence, Mechanical and electrical equipment failure, Computer simulation, Agent system, D-S evidence theory, Hierarchical fault diagnosis model

1. Introduction. Modern mechanical and electrical equipment has a higher degree of automation than ever before, and as its size and complexity increase and its subsystems become more closely correlated, these factors all contribute to an overall increase in automation. As a result, diagnosing equipment faults has never been more challenging [1]. The likelihood of failure has also substantially enhanced, and its expressions are numerous. A problem source may also set off a chain reaction that results in more failure. Additionally, modern businesses now strive to achieve safe and stable functioning of large-scale, complex electromechanical equipment, early fault prediction, predictive maintenance management, and minimization of economic losses brought on by faults and maintenance. Finding appropriate condition monitoring and fault diagnostic methods is, thus, a significant study area for scientists and technology professionals. The study of robots, language recognition, picture recognition, natural language processing, and expert systems all fall under the umbrella of the computer science subfield of artificial intelligence (AI). The science and technology behind AI have advanced significantly since its inception, and its range of applications is likewise growing [2].

Saufi et al. (2019) once developed a solar array model to simulate potential fault types in the real functioning of the array and gather fault data. Four rows and three columns of simulated photovoltaic arrays were established in the computer in accordance with the extensive study of the power generation principle and array connection structure of photovoltaic cells, combined with the on-the-ground investigation in Zichuan Xinmingzhu Photovoltaic Power Generation Center. Based on research into the factors that lead to array failures, a failure operation state was simulated, the output characteristics of the array in each failure state were compared to those in the normal failure-free state, and real-time failure operation data were acquired [3]. Using this information as a foundation, Park et al. (2020) proposed a stacked method of creating a countermeasure network to address the issue of imbalanced categories in fan data sets. They also carefully took into account the correlation and timing of fan data characteristics when creating new samples. Using this technique, data is

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generated gradually while maintaining both the strong and weak correlations between attributes. Additionally, while the cyclic neural network is built, the generators and discriminators for the countermeasure network are formed, and the time series properties of the data are recorded. The random forest technique is employed in the background to filter out the highly significant characteristics, which lowers the difficulty of model development and speeds up model training.

The model is broken down into two stages: in the first stage, samples are trained in groups according to the findings of the analysis of correlation coefficient and maximal mutual information coefficient, and feature subsets of the appropriate groups are formed. The poor correlation between the features of each group is adjusted to provide minority sample data with high simulation in the second step, where each group of feature data obtained in the first stage is spliced as input [4]. In addition to using neural networks, Qiao et al. (2019) improved the K-nearest neighbor approach and created sub-blocks using the mutual information between variables to extract the local information of the process, resulting in more identical information for the variables in the sub-blocks. Based on this, a defect detection model using the K closest neighbor approach is created for each variable sub-block, and the Bayesian inference method is utilized to combine the detection findings of each sub-block, improving the overall detection effect. Additionally, the Mahalanobis distance-based fault diagnosis method is used.

The source variable generating the error is identified and isolated by computing the Mahalanobis distance between each variable in the sample and its mean value. Final evidence that this method has a greater warning rate than the conventional fault detection method comes from the Tennessee-Hysmans process simulation experiment [5]. Ju et al. (2021) presented a fault detection method of generative countermeasure network with coded input to address the issue that the standard fault detection method based on generative countermeasure network uses random noise as generator input and the network training impact is not good. After dimension reduction, the hidden variable information is used as the input to the self-encoder, which is then introduced. In order to address the issues with defect detection methods' high computation costs and sensitivity to outliers, a novel statistical calculation method based on self-hidden encoder's variable extraction is proposed. The simulation results using the Tennessee-Hysmans process and real coal mill process demonstrate that the suggested strategy can enhance the network training effect [6].

Based on the foregoing context, this paper first introduces Agent and its system and describes its use and flaws; Second, a description of the hierarchical fault diagnosis model is provided, along with optimization recommendations. Thirdly, the classical model is optimized by mixing neural networks, and the Dempster-Shafer (D-S) theory is briefly explained. Finally, comparative experiments are used to confirm the validity and effectiveness of this approach.

2. Establishment of computer simulation model for electromechanical equipment.

2.1. Agent and Agent system. One of the most significant research areas in the field of artificial intelligence is agents and agent systems, which has a wide range of potential applications. Although the concept of an agent has long been debatable, all academics concur that agents have autonomy. The notion of Agent is therefore utilized to define what is considered to be a conscious intelligent system, and cognitive elements like belief, ability, intention, and commitment in the process of human activity are used [7,8]. Figure 2.1 depicts its composition and model structure.

Agent is an abstract word that can represent all sentient entities. It is also known as the Belief Desire Intention (BDI) model. It can be used to describe not only robots but also intelligent software, objects, and people. Typically, an agent exists in an environment, observes the environment using its own sensors, and then acts on the environment using effectors. Even if a single agent is active and autonomous, it is unable to exist in the environment on its own and must interact with other agents there in order to complete its tasks. The Agent's structure specifies the components that make up the agent, how the components communicate with one another, and how the agent is implemented using hardware and software.

Deliberate agents make decisions through logical deduction, reactive agents make decisions through direct mapping from scenarios to actions, and hierarchical agents make decisions through BDI. In general, the structure of agents can be divided into the following four types: reactive agents, BDI agents, deliberate agents, and hierarchical agents. In order to make decisions, BDI agents operate data structures that reflect their beliefs, wishes, and intentions, while hierarchical agents use various tiers of software, each of which partially implements

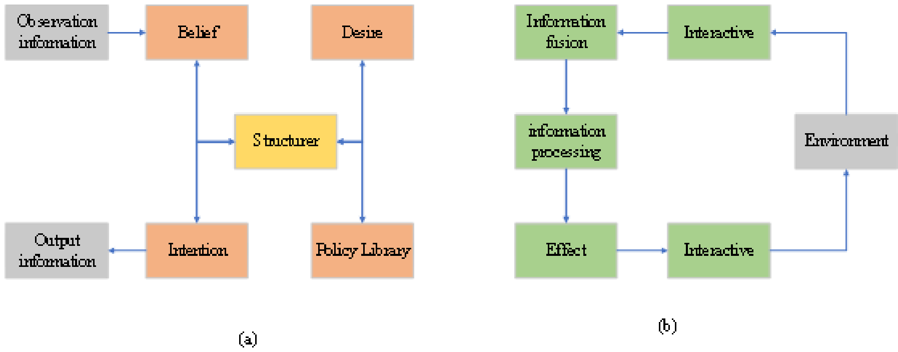

Fig. 2.1: Agent composition and structure diagram (a) Agent composition; (b) Agent structure diagram

reasoning about the environment. The thinking Agent is the most frequently employed of these four categories. Due to the complexity of the multi-agent system environment, each agent's information about the environment differs in the distributed fault diagnosis system for large-scale complex electromechanical equipment. Information fusion technology can be used to process numerous data sources, and the collaboration of different agents can lead to more thorough and accurate problem diagnosis results.

The developed multi-agent system uses a variety of sensors to gather data, which is then processed in a consistent format before information fusion is performed. Additionally, the system's agents can communicate with one another to collaborate and coordinate, creating a stable and effective system. The multi-agent system is broken down into three layers in this paper through analysis: the data processing layer, the primary diagnosis layer, and the information fusion layer. These layers each contain several roles [9,10]. Because Agent roles' duties vary, it is necessary to model them in accordance with the tasks that each position is responsible for. Figure 2.2 depicts their structures:

The foundation of the system environment, which is used to gather the system's original signals, is the data collection agent. To provide the system with the preprocessed original environmental information, the information processing agent preprocesses the original signal and applies various feature extraction techniques depending on the task scenario. The major duties of the data collection and information processing agent include gathering machine state data and giving the diagnosis system the original data. In multi-agent systems, the Management Agent is crucial for understanding the overall state of the entire system. Establishing the job, mastering the evaluation criteria for the breakdown of diagnostic tasks, assessing the diagnostic agents in the system, and formulating cooperation rules as the cornerstone for efficient coordination and collaboration among agents are some of its special functions [11]. Neural networks make up all different types of defect diagnosis agents, and each diagnosis agent has a unique diagnosis technique. They are able to fulfill the diagnosis function in accordance with the circumstances by extracting features from the original environmental information. Their specialized duties include receiving information from information processing and data gathering agents in accordance with the properties of environmental information. Accept the management agent's orders and carry out the tasks in accordance with the specifications and its own algorithm.

2.2. Hierarchical fault diagnosis model. The original signal is captured by the data collection agent in the agent system, and the feature is extracted by the information processing agent. The management agent executes global management, selects the appropriate data collecting and information processing agents, and decides the necessary diagnosis approach based on the job scenario. Next, a variety of tasks are assigned, and then various diagnosis agents are chosen depending on the contract network's bids. The specific fault diagnosis analysis then gets underway [12]. Figure 2.3 illustrates its hierarchical structural model.

This paradigm, which is abstract in nature, can be used to create distributed fault diagnosis systems for a variety of intricate electromechanical devices. However, the deployment of this paradigm must vary for various application contexts and diagnostic objects. The main challenge for the practical implementation of the model

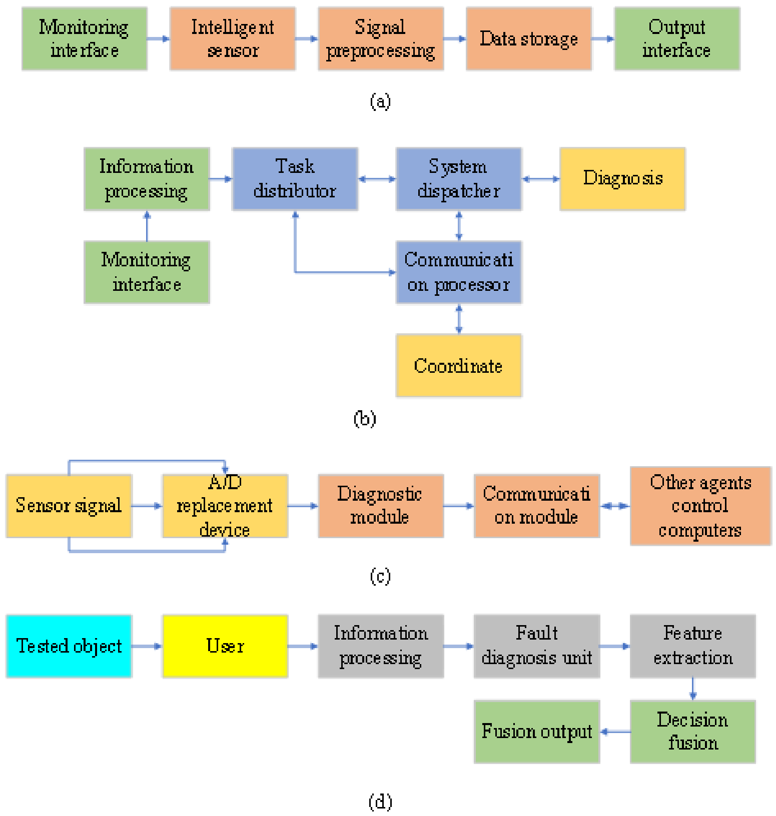

Fig. 2.2: Composition of roles in Agent model (a) Data acquisition and information processing structure; (b) Internal structure of management agent; (c) Fault diagnosis internal structure; (d) Fault diagnosis fusion structure

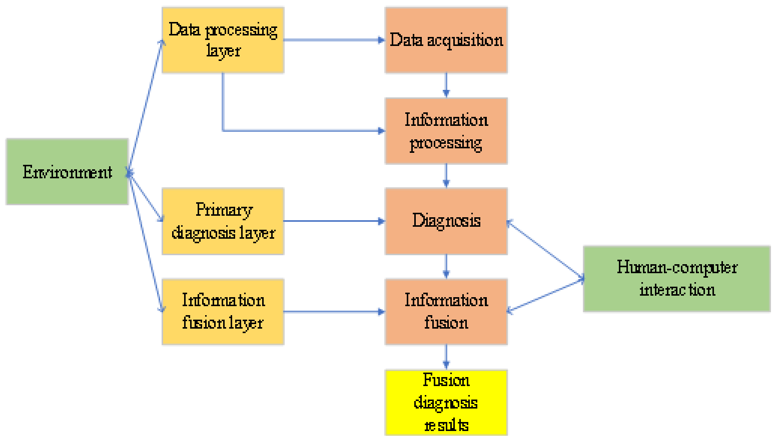

Fig. 2.3: Multi-level structure model

is to address its adaptability, or the flexible deployment of the model in various applications. A large-scale, intricate electromechanical system is made up of many different subsystems, and each subsystem has a large

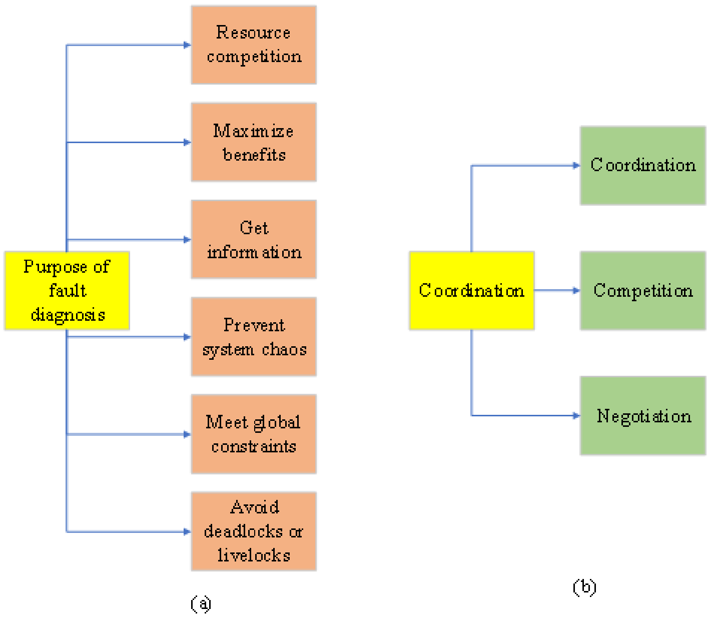

Fig. 2.4: Cooperation mode and purpose (a) Purpose of collaboration; (b) Collaborative approach

number of devices. Each gadget varies in complexity and has a number of parts. An efficient solution to address the system's overall state monitoring, fault diagnosis, and predictive maintenance is to build a distributed fault diagnosis system using a multi-agent system. However, the architecture and locations where devices are put vary amongst various complex systems. Important issues in practical application include how to design computers to properly monitor various devices, how to deploy various Agent on the network, and how to establish up a monitoring network in accordance with the unique characteristics of various systems [13].

Modern mechanical equipment fault diagnosis has gone through a number of stages, including distributed online diagnosis, remote distributed diagnosis, single-machine online diagnosis, centralized online diagnostic, and off-line diagnosis. There are benefits and drawbacks to each step. One of them, off-line fault diagnosis, has the advantages of economy, convenience, and flexibility, but the drawbacks are that it cannot fully obtain mechanical equipment operation information and cannot resolve single-machine on-line fault diagnosis in time when encountering sudden faults, not to mention that it is too expensive. While sharing information and saving money are benefits of centralized online fault diagnosis, real-time diagnosis is not very good. The advantages of distributed online fault diagnosis include strong real-time performance and inexpensive costs, but the drawback is that the system as a whole is not flexible [14].

The study of AI is currently focused on distributed artificial intelligence (DAI), which uses several agents. Studying the cooperation between several Agents is thus a crucial task in distributed AI systems. It can work together to accomplish tasks that a single Agent cannot. Figure 2.4 illustrates its cooperation strategy and goal.

The interaction between diagnostic agents and fault information as it exists now, as well as the coordination and collaboration among diagnostic agents, are all part of online network fault diagnosis. Due to the intricacy of the diagnosis task, the distributed fault diagnosis system's fault diagnosis agents are dispersed across several geographic regions and must collaborate with one another to perform the mission [15]. It is common for Agents with varying expertise and skills to work together to complete diagnostic tasks. Task distribution can be a dynamic process including ongoing dialogue, and the completion of the overall task is ensured by the release of each subtask. The contract network protocol should be used for negotiation during this process.

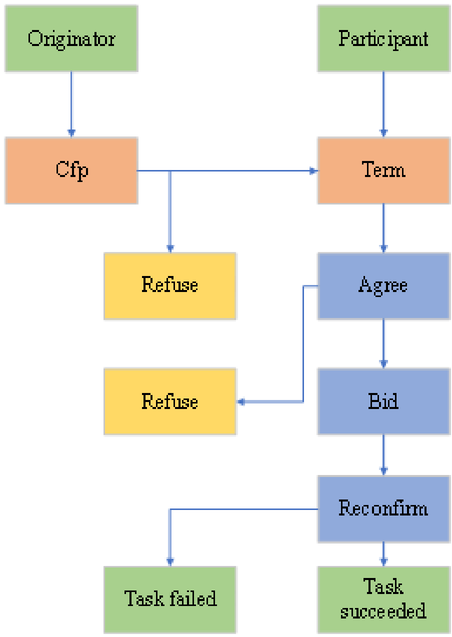

Fig. 2.5: Optimized sequence diagram

2.3. Contract net model. The contract net concept is the most well-known technique of collaboration. The fundamental tenet of the contract net model is that tasks are assigned by competitive bidding among Agents, and that tasks are distributed and bargained during the competitive bidding process utilizing a communication system. There are four basic stages to the collaboration process based on the traditional contract network: First, the task initiator notifies the task participants of a tender request. Second, the task participants respond to the initiator's request within the allotted time frame and those who do not respond within that time frame assume that they will give up bidding. Thirdly, the task initiator chooses one or more successful bidders, notifies those who have won the bid, and notifies those who have not. The participants that won the bid eventually respond that they failed and were eliminated [16]. The time required can be estimated if there are numerous task initiators and participants with limited resources, and if the next task can only be negotiated after each task is finished in a first-come, first-served order. The task execution pace will be significantly increased, nevertheless, if these tasks are negotiated simultaneously to the fullest extent possible, taking into account each Agent's capabilities [17].

In order to efficiently utilize the resources of each Agent, this study proposes the Contract Net Protocol Based on Posting Commitment Time (P-CNP). Figure 2.5 displays the timing diagram that has been optimized.

At this point, the sponsor assesses the applicants, places them in a queue, and then prioritizes sending the inquiry information, reconfirming the bidder's ability to actually accomplish the assignment. It transfers the query information to the next participant when the person being queried provides the rejection information or goes beyond the minimum time limit, which can save a ton of time and system resources [18].

2.4. Fault diagnosis method based on multi-layer spatio-temporal information fusion. The target of mechanical defect detection now exhibits several novel properties such as time-varying, nonlinear, lagging, complexity, and fuzziness due to the ongoing advancement of modern science and technology. It frequently happens that every type of problem occurs at the same time when a system malfunctions. As a result, there will be several occurrences like erroneous identification and omission if people attempt to monitor the working conditions and detect the various defect characteristics in complex systems just using theoretical methods and information [19].

Making the performance of the entire information system greater than that of the component subsystems

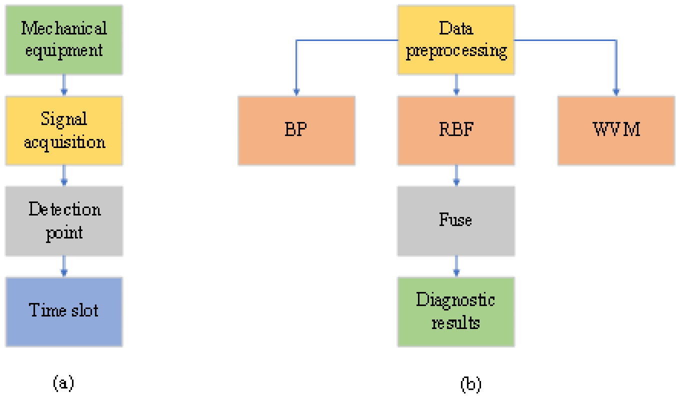

Fig. 2.6: Multi-layer spatiotemporal domain information fusion fault diagnosis model (a) Data acquisition model; (b) Diagnosis and fusion model

is the fundamental idea behind and place where information fusion begins. Their redundant or complementary information in time or space is reasonably merged according to specified criteria through the logical control and utilization of numerous information sources [20]. In the fault diagnosis system, the fusion technology of multi-sensor information can increase the fault diagnosis accuracy of the system, improve the accuracy of state estimation, improve the detection performance and increase the reliability of diagnosis results, and maximize the scheduling of the system and the utilization of information resources based on sensor resources. As a result, a novel Multi-Tier Time Space Domain D-S Information Fusion Diagnosis Model (MT-TS-DS) model is developed by incorporating neural networks with D-S evidence theory.

In the process of diagnosing a specific fault, samples are taken at adjacent time intervals of the same monitoring point, the features are extracted, and the results of the diagnosis are given in order to avoid the diagnosis uncertainty brought on by different sampling times at the same monitoring point of the same piece of equipment. The results from various time periods are then combined using D-S fusion as the foundation for the aforementioned spatial fusion. This multi-layer time-space D-S information fusion defect diagnosis technique employs neural networks and D-S evidence theory. Figure 2.6 displays the diagnostic model for it.

Its sub-neural network local diagnosis process is primarily focused on the various operation state information of mechanical equipment in various time periods. It uses various sensors to collect the operation data of the equipment and then extracts the fault information's characteristics through time domain analysis and wavelet decomposition, creating various fault feature vector spaces and corresponding fault type spaces. Then, for each defect feature vector space and related fault type space, a matching neural network is built, and it is trained using experimental samples. The parameters, such as training duration and training times of each neural network, are received during the test for each trained sub-neural network, which supplies the D-S information fusion with the essential parameters. The goal of the global diagnosis is to compile the findings from each neural network's diagnosis in one place. This allows the D-S evidence theory's evidence space to be generated, and numerous diagnosis findings in the same operating state can be considered different evidence components. The identification space is then built according to the different equipment fault types, and the basic probability assignment function is used to determine the potential probabilities of each fault type. The diagnosis conclusion is then reached after applying the D-S evidence theory fusion rule to determine the probability distribution of the total failure type based on the failure type probabilities of each D-S evidence element.

The most crucial stage is to analyze and handle the motor fault signal after it has been captured by the fault signal acquisition system. The feature vector of the fault signal is created after the fault signal has been extracted using time domain analysis and wavelet decomposition, and it is used as the input vector of the following neural network. The fault signal's characteristic vector, which is susceptible to non-stationary signals, is taken into account by the time domain analysis method using the parameters of the time domain amplitude domain. The mechanical equipment fault signal is divided by the wavelet analysis method into numerous

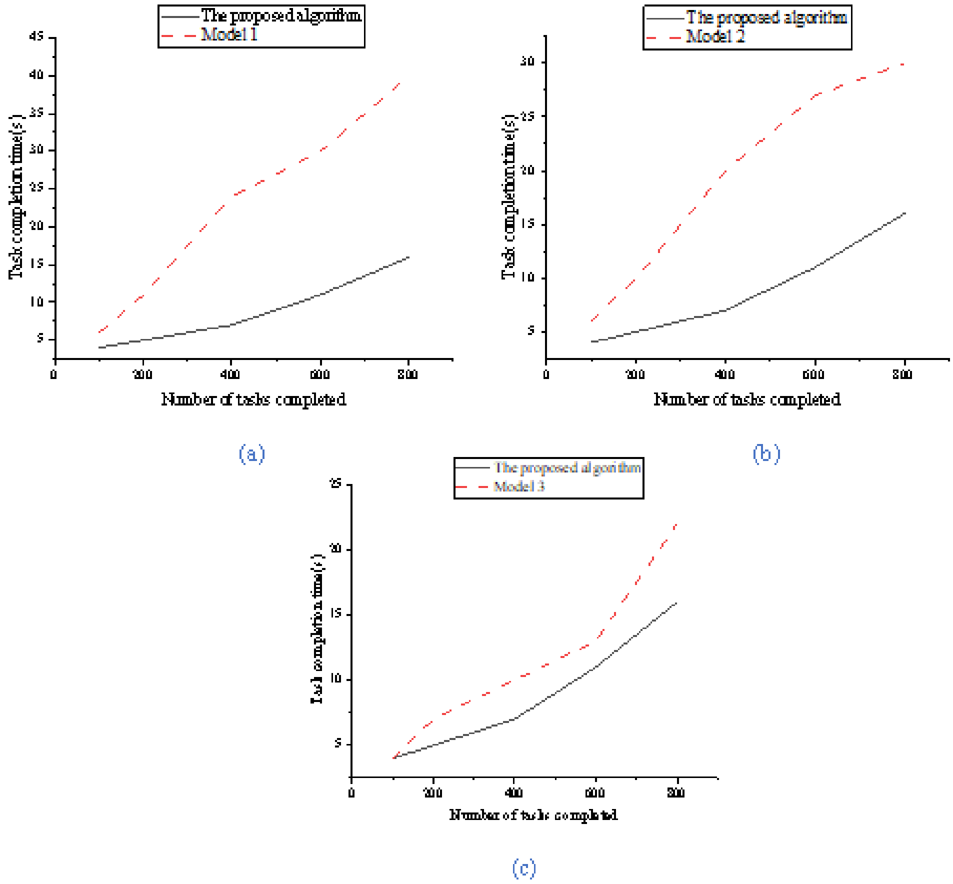

Fig. 3.1: Comparison of task completion time (a) Comparison between the proposed model and model 1; (b) Comparison between the proposed model and model 2; (c) Comparison between the proposed model and model 3

independent frequency bands, and each band's energy is then sent to the neural network as an extracted feature vector. Both time domain analysis and wavelet decomposition are effective techniques for extracting features from mechanical defect signals.

3. Comparison of experimental results between computer simulation optimization of electromechanical equipment.

3.1. Comparison of task completion time results between traditional model and optimization model in this paper. The number of Agents is set to 20, and the number of tasks is set to 100, 200, 400, 600, and 800. In this paper, model 1 is a traditional model, model 2 is an access policy base model, model 3 is a model with task parallel processing and a delay waiting mechanism, and model 4 is an optimized model. Figure 2.7 depicts their comparative experimental results.

According to Figure 3.1, under the same number of tasks, the time required to complete the task is the shortest, and as the number of tasks increases, the time increase rate of the optimization algorithm in this paper is also the slowest, which is more stable than the traditional model. According to their data, model 1 and model 2 take longer to complete tasks than model 3 and this model, which also demonstrates the benefits of multi-party task processing and can significantly save space resources and time loss in the environment of secondary confirmation.

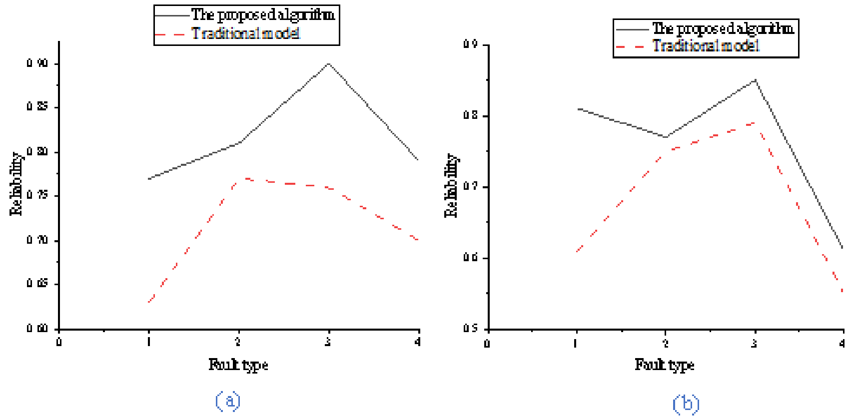

Fig. 3.2: Credibility comparison (a) Comparison of the results of the traditional model and the proposed model in sample 1; (b) Comparison of the results of the traditional model and the proposed model in sample 2

3.2. Comparison of reliability of fault diagnosis results between traditional model and this model. As samples, two types of mechanical and electrical equipment fault information are chosen, with the equipment cracking being 1, the equipment aging being 2, the functional failure being 3, and the excessive pressure being 4. Finally, their dependability is determined. Figure 3.2 depicts the experimental results.

Figure 3.2 shows that the reliability of the optimized algorithm in this paper is higher than that of the traditional model, with the highest reliability being 0.91 and the lowest being 0.63, but it is also higher than the traditional model's recognition rate. Meanwhile, the model in this paper has the highest reliability in identifying functional failure, according to the image, because the model in this paper is diagnosed using a neural network. If the failure information is not responded to, it is automatically deferred to the next information. Because functional failure causes errors in subsequent information data, the model has a higher recognition degree of functional failure.

4. Conclusion. A wide range of cutting-edge technologies can be used in conjunction with the broad utilization of mechanical and electrical equipment. AI is one of the most commonly used technologies in mechanical and electrical equipment, and current research is focused on using computer simulation to conduct experiments to identify mechanical and electrical equipment defects. As a result, this paper begins by introducing Agent and the Agent system, then goes on to detail Agent's current applications in mechanical and electrical equipment, explain the hierarchical fault detection model and its current drawbacks, and finally propose an optimization strategy. To increase the efficiency of this model's computation, the contract net model is once more detailed and added to the optimization model in this work. The dependability and logic of this model are then tested through trials before the multi-temporal spatial information fusion diagnosis technology is integrated into the model. The experimental findings demonstrate that the optimized model in this research runs at a significantly higher speed than competing models when subjected to the same workload, demonstrating the model's efficacy. The ability to multitask can shorten the model's running time, as seen by a comparison of Models 1, 2, and 3. In the second experiment, samples of mechanical and electrical equipment defect data are taken from two groups. The experimental findings demonstrate that the optimized model in this work can have a reliability between 0.63 and 0.91. The reliability of the four fault types predicted is substantially higher than that of the conventional model, demonstrating the soundness of the model used in this paper.

This paper also suffers from a number of flaws. On the one hand, the MT-TS-DS model completes multi-source information fusion using neural network technology and D-S evidence theory, and the fusion effect is ideal. On the other hand, other intelligent information processing technologies, such as support vector machines, have not been considered, and the fusion of other technologies will be taken into account in subsequent research. Nonetheless, the fault diagnosis experiment in this work only takes into account four fault kinds; however, future research will also enhance the corresponding problem categories, increasing the experiment's credibility.

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