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Energy Efficiency Optimization of Industrial Internet of Things and Predictive Maintenance of Equipment

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ABSTRACT

This study aims to explore the key paths for energy efficiency optimization and predictive maintenance of equipment in the industrial Internet of Things (IoT) environment. In response to the challenges such as low utilization of on-site industrial data and the difficulty in balancing the real-time performance and economic efficiency of algorithms, modern industries mainly adopt solutions including association rule algorithms and neural network algorithms, and construct a collaborative architecture of "edge real-time perception + cloud global optimization". Meanwhile, to verify this method, the author designed a simulation scheme: taking the data from an engine factory as the object, the Apriori algorithm was used to mine the association rules of parameters such as temperature, humidity, and power, and a BP neural network dynamic prediction model was constructed. The parameters were optimized through gradient descent, and the effectiveness of the model in reducing unplanned downtime and energy consumption was ultimately evaluated, providing empirical evidence for industrial applications.

KEYWORDS

Industrial internet of things; Associaton rule algorithm; Neural network algorithm; Clanguage simulaton; Future development

1 Introduction

With the advancement of the global "dual carbon" goals and the deepening of industrial digital transformation, the industrial Internet of Things needs to enhance energy efficiency. At the same time, to save costs, equipment also needs to achieve efficient predictive maintenance. The multi-source data generated by industrial equipment during operation contain rich state information. Through intelligent algorithms for analysis and modeling, it is possible to shift from "repair after failure" to "intervention before failure", significantly improving equipment reliability, resource utilization, and energy efficiency. However, current industrial sites still face challenges such as poor data quality, limited computing power, weak model generalization ability, and insufficient system collaboration. There is an urgent need to research more applicable and real-time optimization methods. This paper aims to systematically study the key technologies and implementation paths of energy efficiency optimization and predictive maintenance in the context of industrial Internet of Things. By using methods such as association rule mining, neural network modeling, and edge-cloud collaborative computing, a lightweight and scalable dynamic prediction model is constructed. The application effects of different algorithms in typical industrial scenarios are compared and analyzed. This research is conducive to promoting the green and low-carbon transformation of industry and has important theoretical value and practical significance in engineering.

2 The significance and research status of industrial IoT optimization

2.1 The significance of industrial IoT optimization

The optimization of energy efficiency in industrial Internet of Things has significant strategic significance in promoting industrial green transformation and intelligent upgrading. In the context of global pursuit of carbon peak and carbon neutrality, high energy consuming industries urgently need to achieve energy-saving and consumption reduction goals through technological upgrades. The Industrial Internet of Things achieves energy conservation and efficiency improvement by real-time monitoring of device status data, including multi-dimensional parameters such as power, temperature, pressure, and head, and establishing intelligent prediction models.

The energy efficiency optimization of industrial Internet of Things has a profound impact on achieving industrial green transformation. Through the organic combination of intelligent perception, data analysis, and optimized regulation, the Industrial Internet of Things can help enterprises implement energy-saving measures, and more importantly, provide a complete energy efficiency improvement solution for high energy consuming industries. This technology application is changing the operating mode of traditional industries and promoting the transformation of industries towards environmentally friendly development. The predictive maintenance of devices driven by industrial Internet of Things utilizes intelligent algorithms to analyze device status data in real time, transforming multi-source heterogeneous information into executable maintenance decisions, achieving an important transformation from post fault repair to pre failure intervention. This data-driven proactive regulation approach not only significantly reduces unplanned downtime, but also effectively reduces energy waste, fundamentally improving equipment operating efficiency and resource utilization. With the continuous development and improvement of related technologies, the application value of industrial Internet of Things in energy efficiency optimization will be further highlighted. It not only responds to the needs of the global sustainable development strategy, but also provides a practical and feasible technological path for enterprises to improve quality and efficiency, reduce emissions and carbon emissions, and plays an important supporting role in building a green, intelligent and efficient modern industrial system.

2.2 Research status in China and abroad

2.2.1 Current research status in China

Domestic research in this field combines application orientation and technological integration. Its main technological innovations focus on edge side lightweight algorithm deployment and algorithm localization, aiming to adapt to the real environment of limited computing power and high data privacy requirements in industrial sites. At the same time, it also pays attention to high energy consuming areas, such as building warning models in non-ferrous metal smelting and rolling processing industries to reduce maintenance costs.

It is worth noting that domestic research has formed an engineering promotion mode of "standard traction algorithm fusion scene closed-loop", emphasizing the deep integration of technology with actual industrial scenarios. A typical representative is the "human information physical system" driving mode developed by Professor Liu Min's team at Tongji University, which has successfully solved the problem of few sample fault diagnosis and applied it to large enterprises; The Ma Shuaiyin team at Xi'an University of Posts and Telecommunications has achieved significant energy-saving benefits through the edge cloud collaborative architecture and mechanism data dual drive method.

However, domestic research still faces many challenges: many factories have insufficient capacity and algorithm integration, and still rely on manual troubleshooting and parameter adjustment, resulting in the inability to detect the root cause of energy consumption in real time; There are problems such as high noise and missing annotations in multi-source data in industrial sites, and the phenomenon of data silos seriously restricts global optimization. At the same time, edge computing power limitations also affect the deployment effectiveness of complex algorithms. In addition, existing systems often separate fault warning and energy consumption control functions, lacking collaborative optimization loops. The gap between high-precision sensing costs and the budgets of small and medium-sized enterprises also restricts technology promotion. Existing factories still need to seek breakthroughs in data fusion, computing power improvement, and cost control to promote the large-scale application of technology.

2.2.2 Current research status abroad

Foreign research in this field has shown a distinct orientation towards fundamental innovation and system integration, with its core advantage being the breakthrough in the original generation of underlying algorithms and the deep integration of hardware software services. The international academic community is highly focused on the cutting-edge exploration of underlying algorithms in artificial intelligence, committed to solving core problems through disruptive theoretical innovation. The thermal collector based on the Seebeck effect developed by Professor Aragones' team at the Polytechnic University of Madrid in Spain is a typical representative. This technology can collect energy from industrial waste heat and supply power to industrial IoT sensing nodes, fundamentally solving the endurance bottleneck of traditional battery power supply equipment in the high-temperature industry. At the same time, NASA's proposed cloud edge end collaborative architecture achieves efficient management from terminal perception, edge processing to cloud optimization, reflecting the comprehensive optimization ability of system reliability, real-time performance, and energy efficiency under extreme conditions. Foreign research has provided system level solutions to address the complexity of multi device collaboration in industrial IoT. The distributed continuous time fault estimation control system developed by Roberto Casado Vara's team at the University of Salamanca combines collaborative control and state prediction technology, providing an effective fault tolerance mechanism for multi device IoT networks. Its innovative Markov chain based intermediate temperature matrix model can seamlessly replace physical equipment failures through virtual devices, ensuring continuous monitoring and data collection, greatly improving the reliability of the entire prediction system. Overall, foreign research has formed a complete structure from basic theory, hardware innovation to system architecture. Its core is to overcome the most fundamental technological bottlenecks in industrial applications through deep interdisciplinary integration. This research approach complements and contrasts with the domestic model that focuses on engineering implementation.

3 Predictive maintenance simulation analysis

3.1 Some core algorithms involved in predictive maintenance

3.1.1 Cloud computing and edge computing

Edge computing and cloud computing efficiently collaborate to achieve energy efficiency optimization through layered collaborative architecture: the edge layer is deployed on the device side, real-time processing sensor data, fault detection, energy consumption anomaly identification and local control decisions, ensuring low latency response to key tasks and reducing bandwidth pressure; The cloud gathers historical data from multiple sources, trains complex models, constructs global device health profiles and energy efficiency benchmarks, optimizes maintenance strategies and production line scheduling through reinforcement learning, and verifies energy-saving solutions based on digital twin simulations.

3.1.2 Association rule algorithm

In predictive maintenance, association rule algorithm is a key data mining technique used to extract implicit associations between multidimensional data items from massive device operating parameters. By analyzing historical data, calculating the support and confidence of different data combinations, identifying frequent co-occurrence fault characteristic patterns, and providing data-driven decision support for maintenance personnel [5-6].

3.1.3 Neural network algorithm for data mining

The neural network algorithm in data mining is the core driving technology for predictive maintenance of equipment, and the two constitute the cornerstone of intelligent diagnosis and decision-making. Deep learning is a subset of neural network algorithms that can automatically learn representations and predictions. It contains three core concepts: activation function, weight, and bias. The activation function determines whether a neuron is activated, weights control the importance of inputs, and biases adjust inputs to predict outputs more accurately.

3.2 Simulation of certain processes in predictive maintenance of equipment

3.2.1 Preprocessing of dataset

The author used the engine maintenance related dataset provided by Kunming University of Science and Technology in the National Basic Discipline Public Safety Center as a basis. Firstly, the dataset was simplified into three aspects: environmental temperature, input power, and environmental humidity. The association rule algorithm was used for

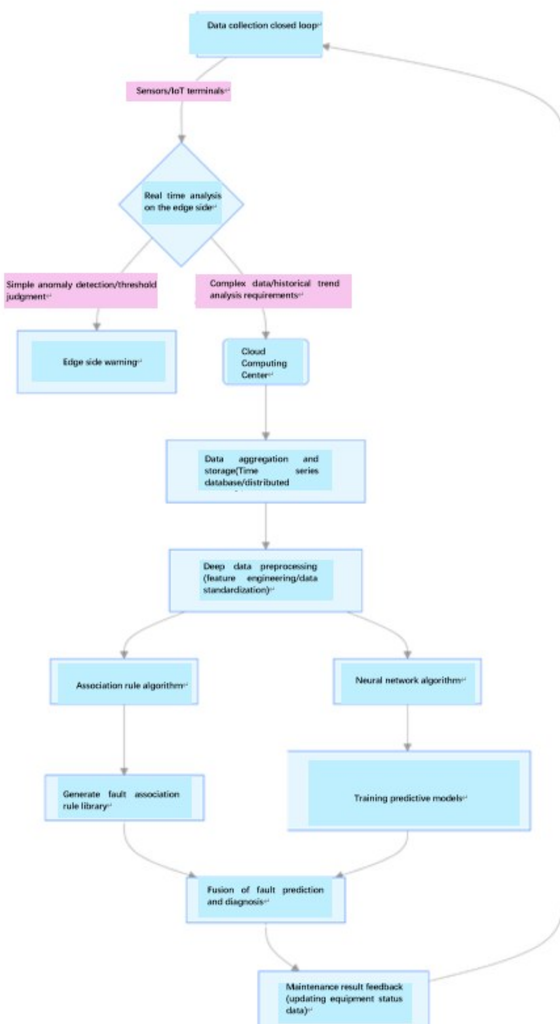

Figure 1 Predictive maintenance process for equipment

preprocessing to determine whether the data were independent of each other, that is, whether they were frequent itemsets when combined together, laying the foundation for adding certain weights to the data later.

The author introduces the Apriori algorithm here. If each subset is exhaustively searched, the algorithm complexity is O (2 ^ n-1). If an itemset is frequent, then all its subsets are also frequent. Using this characteristic for pruning and optimizing complexity, 14 frequent terms were obtained, including 5 binary terms and their respective subsets.

3.2.2 Dynamic model simulation

Before using the Bp neural network, the author attempted two alternative methods, including binary search trees (i.e. directly inputting all datasets for querying) and calculating weighted parameters, similar to Na ï ve Bayes, referencing whether each data appears frequently and assigning weights to calculate a parameter for each dataset, which is continuously adjusted as the dataset is read in.

These cannot meet the requirements of the so-called dynamic model, so the author adopted a method of reducing the types of input data or introducing a simple BP neural network to determine the number of three input layer nodes based on the number of input features. The output layer is set according to the task: if it is classified as a fault such as normal, warning, or fault, the Softmax function is used to output the probability of each category, and 1-2 hidden layers are used. Subsequently, the preprocessed dataset is divided into a training set, a validation set, and a testing set. Using training set data as input to the network, the weights and biases in the network are iteratively updated through backpropagation algorithm combined with gradient descent to predict the loss between the output and the true labels. Finally, the validation set is used to monitor the training process and prevent overfitting.

In the end, the trained BP neural network model becomes a nonlinear mapping function that can learn complex hidden relationships between environmental temperature, input power, humidity, and engine health status. The author compared the remaining thousands of data points into a dynamic model with two other methods, and the results were completely consistent with the predicted results of the search tree, while there were 8 different predicted results from the dynamic parameter model.

3.2.3 Experimental Conclusion

The neural network algorithm centered on BP neural network can save a certain amount of space complexity and time complexity, and no obvious experimental errors have been found. At the same time, combined with the simulation of the entire process, it can be clearly concluded that compared with traditional industrial predictive maintenance, the introduction of this dynamic model can achieve a dual improvement in reliability and energy efficiency.

4 Conclusion

4.1 Analysis of algorithm application scenarios

The application scenarios of various algorithms in predictive maintenance show significant differences based on industrial requirements and data characteristics. Association rule algorithms are mainly applied in multi parameter coupled analysis scenarios, such as mining implicit relationships between environmental temperature, cooling water pressure, and generator winding temperature in thermal power plants. Convolutional neural networks perform outstandingly in image and spectral pattern recognition scenarios, and are suitable for precision diagnosis of rotating machinery. For example, in the wind power industry, CNN is used to analyze gearbox vibration spectrum images. Long short-term memory networks focus on degradation prediction scenarios with strong temporal dependencies. For example, predicting the remaining life of aircraft engines is a typical application. LSTM captures performance degradation trajectories and accurately predicts maintenance windows by analyzing historical operating parameter sequences [7-8].

Various algorithms are implemented through cloud edge collaborative architecture: lightweight algorithms are deployed on the edge side for real-time diagnosis, and complex models are deeply trained and optimized in the cloud, ultimately forming a complete maintenance system. This multi-level technical architecture enables predictive maintenance to adapt to diverse application scenarios from discrete manufacturing to process industries.

4.2 Comparative analysis with traditional industries

Modern predictive maintenance has undergone fundamental changes in technology, decision-making, and implementation effectiveness compared to traditional predictive maintenance. Traditional methods mainly rely on regular inspections, threshold alarms, and experience based fault diagnosis. Their essence is to repair on time or after the fact, which has the drawbacks of insufficient or excessive maintenance and cannot effectively avoid unplanned downtime and energy waste. Modern predictive maintenance, driven by industrial Internet of Things, big data, and artificial intelligence technologies, has achieved condition based maintenance[9-10].

Traditional methods use simple vibration analyzers and temperature sensors for offline detection, resulting in isolated data and lagging analysis; Modern methods deploy multi-source sensor networks to collect high-frequency time-series data such as device vibration, temperature, current, and environmental parameters in real-time, and rely on edge cloud computing architecture to achieve data fusion processing. Far beyond the capability boundaries of statistical analysis.

4.3 Outlook and analysis of the future

There is still a lot of room for improvement in the existing predictive maintenance industry, including algorithm flaws, inability of small and medium-sized enterprises to afford high-precision sensing costs, difficulties in processing datasets, and so on. In response, scientists have proposed a series of solutions, including cloud edge collaborative training and model lightweighting technology; The universalization of lightweight edge devices, the introduction of stream processing engines, and so on, however, there is still a long way to go for energy efficiency optimization in industrial IoT.

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