Design and Implementation of Cost Management System for Mobile Mining Equipment Based on IoT and Multi - objective Optimization Algorithms

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***Abstract*—In the accelerating modernization of the mining industry, cost management has emerged as one of the core drivers of industrial development. This paper centers on the cost management of mobile mining equipment, devising a system integrating the Internet of Things (IoT) and multi - objective optimization algorithms. By equipping mobile mining equipment with various sensors to build an IoT architecture, real - time data collection and transmission of equipment operations are achieved. Leveraging multi - objective optimization algorithms, a cost - optimization model is established, taking into comprehensive consideration factors such as equipment maintenance costs, energy consumption costs, and production efficiency. This model enables data processing, analysis, and optimized decision - making for the equipment. It effectively enhances the management efficiency of mining equipment, cuts costs, and boosts production stability. The system offers an efficient cost - management solution for mining enterprises and is of great significance in promoting the intelligent development of the mining industry.**

Keywords-Cost Management; Multi-objective Optimization; Internet of Things(IoT);

I. Introduction

The rapid global economic and technological integration has put the mining industry at a crucial transformation and upgrading point. Traditional equipment management models face challenges due to numerous, wide - spread devices and complex operating environments. Manual inspections and experience - based judgments can't accurately assess equipment conditions, causing frequent failures that disrupt production, waste production time, affect resource supply, and incur high repair costs in labor, materials, and finance. This leads to low resource - allocation efficiency, long equipment idleness, uncontrolled energy consumption, and increased waste and cost pressures.

The advent of Internet of Things (IoT) technology offers revolutionary opportunities for mobile mining equipment cost management and is vital for enhancing industry competitiveness[1]. Installing sensors and intelligent hardware on equipment enables real - time data collection and transmission, ensuring data timeliness and accuracy. Artificial intelligence algorithms facilitate intelligent fault diagnosis and prediction, allowing for preemptive maintenance strategies, thus avoiding sudden failures and improving management efficiency and precision.

The system's construction and application will benefit mining enterprises in multiple ways. In equipment management efficiency, it enables lifecycle information management of mobile mining equipment, ensuring precise monitoring and scientific management from procurement to disposal. This helps detect and resolve faults promptly, control repair time and costs, boost equipment utilization and reliability, and maintain production continuity, reducing production interruptions and economic losses.

For production cost control, optimizing operational parameters and scheduling strategies can cut energy and raw - material consumption. Precise maintenance plans minimize unnecessary repairs and component replacements, reducing maintenance costs. Rational scheduling also improves production efficiency, shortens idle time, and achieves efficient resource allocation, lowering costs and enhancing economic benefits and competitiveness.

II. Related Theories

A. IoT Technology for Mobile Mining Equipment

In the mobile mining equipment system's sensor layer, high - precision pressure sensors are used to monitor the hydraulic system pressure, reflecting the operational load according to the equipment's characteristics[7]. Vibration sensors are installed on key transmission components like motor shafts and reducers to detect vibration frequency and amplitude, providing early mechanical failure warnings. Energy consumption sensors measure electrical power consumption in real - time for energy usage monitoring[8]. These sensors connect to the data

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acquisition terminal via wired or wireless means to aggregate data.

For network transmission, MQTT communication technology packages data like vehicle load, fuel level, and engine operating hours in JSON format and sends it to the MQTT server. MQTT's low - overhead, low - bandwidth, and reliable - transmission features[9] ensure timely and stable data transfer in complex mining environments. For electric shovel electricity meter data collection, a 4G network card is used for public wireless transmission. Taking advantage of 4G networks' wide coverage and relatively fast speed, this enables automatic collection and remote transmission of electric shovel energy consumption data, meeting remote monitoring and management needs.

B. *Principle of Multi-objective Optimization Algorithms*

Mobile mining equipment cost maintenance multi - objective optimization is based on the multifaceted nature of its costs[4]. These span maintenance costs (routine upkeep, repairs, spare parts), energy consumption costs (affected by operating parameters), and production efficiency (impacting unit product costs and delivery). The key benefit is finding Pareto optimal solutions, offering comprehensive trade - offs for decision - making.

In practice, objectives are turned into functions, and algorithms like genetic algorithms search for optimal solutions. These adapt to equipment status and external changes. Multi - objective optimization can also integrate with scheduling and other systems for coordinated optimization[11]. This balances short - and long - term corporate goals, shifting from single - dimensional to multi - dimensional, system - level cost management. It gives mining companies scientific decision - making support, aiding cost control and efficiency improvement.

III. System Design

A. *Overall System Architecture Design*

The system is generally divided into four layers, as depicted in Figure 1:

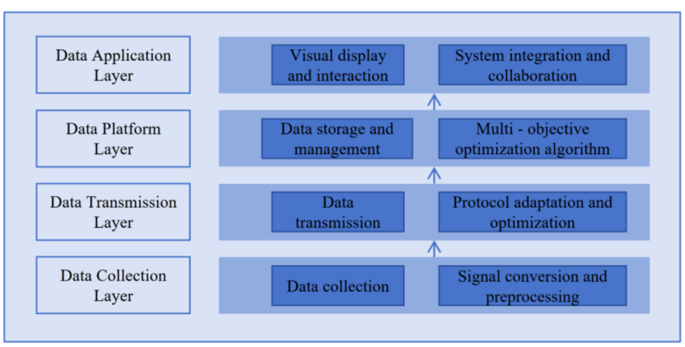

Figure 1 : The four - layer architecture of the system

1) *Data Acquisition Layer*

The Data Acquisition Layer is at the very bottom of the entire architecture[2] and serves as the entry point for obtaining equipment data. It is tightly integrated with mining equipment using a variety of technologies. Through a precise sensor network, various types of sensors are accurately deployed at key locations on the equipment. These sensors include temperature sensors, pressure sensors, vibration sensors, and more. They are capable of real-time monitoring of the equipment's operational status and converting the collected analog signals into digital signals[11]. Moreover, by employing mature industrial automation communication protocols, the layer ensures seamless integration and stable communication with equipment of different brands and models[5]. It also performs preliminary processing and validation of the collected data, providing a high-quality data foundation for subsequent data transmission.

2) *Data Transmission Layer*

The core function of the Data Transmission Layer is to ensure stable and efficient data transfer between different levels of the system[10]. It primarily relies on Industrial Ethernet to establish a robust backbone network architecture. With its high bandwidth and low latency characteristics, Industrial Ethernet provides a reliable physical link for data transmission. Simultaneously, wireless communication technologies are employed to achieve rapid and accurate data transmission from remote equipment, ensuring that data can be promptly transferred from the data acquisition devices to the data processing center.During the data transmission process, specialized message queue protocols such as MQTT and AMQP are utilized. These protocols feature asynchronous message processing and data caching capabilities[3]. In the event of temporary network fluctuations or congestion, the message queues can temporarily store the data and resume transmission[6] once the network is restored. This effectively prevents data loss and ensures the reliability and real-time nature of data transmission.

3) *Data Platform Layer*

The Data Platform Layer is crucial in the system, undertaking two core functions: data storage and management, and multi - objective optimization. For storage and management, a hybrid database architecture is employed. Relational databases store the structured information of equipment, facilitating querying and business processing. Non - relational databases handle semi - structured and unstructured data, conforming to the characteristics of IoT data. Meanwhile, data security and reliability are ensured through backups, encryption, and quality monitoring. In terms of multi - objective optimization, aiming at the multi - objective nature of cost management for mobile mining equipment, a model is constructed, and objectives are transformed into functions[12]. Algorithms are used to find Pareto - optimal solutions, calculate economic indicators, and provide trade - off schemes for decision - making.

4) *Data Application Layer*

The Data Application Layer, as the layer directly facing users and business operations, provides a variety of rich functions and services. Through an intuitive and user-friendly visualization interface, it clearly presents to management and operational personnel the equipment's operating parameters (such as real-time temperature, pressure, and rotational speed), health status (displaying whether the equipment is operating normally and whether there are potential fault risks in the form of charts or indicator lights), and production reports (such as statistical reports on daily output, monthly output, and equipment utilization). This enables them to intuitively understand the equipment's operating conditions and production progress, providing timely and accurate basis for decision-making. Meanwhile, based on advanced technologies such as Web API, it provides external data service interfaces. These interfaces follow standardized specifications and protocols, allowing convenient integration with other information systems within the enterprise. Through these data service interfaces, data sharing and business collaboration between different systems are realized, thereby improving the overall operational efficiency and management level of the enterprise.

IV. SYSTEM IMPLEMENTATION

A. Selection and Deployment of Hardware Devices

The server system is required to be equipped with dual network cards, which are used to connect to the Card - tuning MESH network and the office network. A VMware virtual machine environment has been established to flexibly allocate storage and computing resources. Relational databases, real - time databases, MQTT servers, data analysis software, visual analysis software, and cost analysis systems deployed on this server provide support for data storage, processing, and analysis of the entire system. The data acquisition terminal is equipped with a CAN interface, which can be connected to the vehicle - mounted CAN communication port to receive the message protocol pushed by the vehicle. It also has installed acquisition and parsing software. The terminal is installed in the cab, and an external gain antenna is used to enhance the wireless network signal strength, ensuring the stability and accuracy of data acquisition.

B. Steps of the Multi - objective Optimization Algorithm

As we can see in Figure 2, the Multi-objective Optimization Algorithm can be divided into the following steps:

1) Initializing the Population from Default Parameters: Set default parameters for the model, such as the depth of the tree, the number of estimators, the learning rate, etc. Randomly generate an initial population based on these parameters. Each individual in the population represents a set of parameter combinations, which serves as the basis for subsequent optimization[14].

2) Judging Whether the Termination Condition is Met: After each iteration, check whether the preset termination conditions are met, such as the maximum number of iterations or the convergence range of the objective function value. If the conditions are met, output the optimal parameter combination and end the algorithm. If not, calculate the population entropy and continue with the subsequent optimization.

3) Generating Offspring with Certain Probabilities Based on the Calculation Result of Population Entropy Calculate the population entropy to measure the diversity of individuals. Perform crossover and mutation operations on the individuals in the population with a probability of α. Crossover involves exchanging some genes of individuals, and mutation randomly changes certain genes of individuals, thus generating offspring with new parameter combinations[13]. At the same time, directly inherit some individuals to the next generation with a probability of (1 - α) to retain excellent parameter combinations.

4) Updating the Generated Offspring into the Population and Iterating Until the Termination Condition is Met Incorporate the newly generated offspring into the population, replacing some of the original individuals to form a new population. Then, judge again whether the termination condition is met. Repeat the steps of calculating the population entropy, generating offspring, and updating the population, and keep iterating until the condition is met and the algorithm stops.

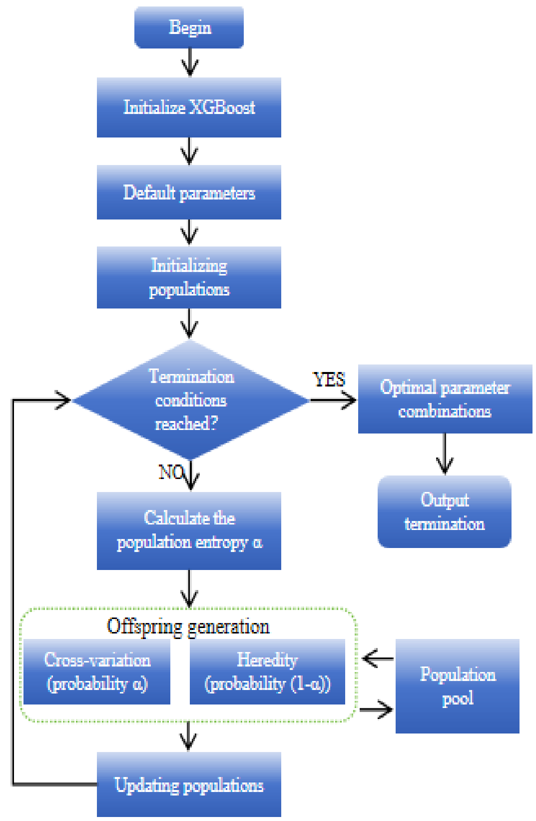

Figure 2. Flowchart of Multi-objective Optimization Algorithm

V. SYSTEM TESTING

A. Data Acquisition and Transmission Testing

Simulate various working conditions on different mobile mining equipment to check the data acquisition accuracy of sensors such as pressure, vibration, temperature, and energy consumption, as shown in Figure 3. Observe the integrity and timeliness of data transmission through MQTT and 4G network cards under different network conditions.

Test Results: Most sensors acquire data accurately under normal working conditions, but under high load, the data of some pressure and vibration sensors fluctuates. During MQTT transmission in a weak signal environment, the data delay increases to 3 - 5 seconds, but there is no data loss. After the network interruption of 4G network card transmission is restored, there is occasionally a small amount of data loss.

Figure 3 : On - site deployment of equipment

B. Data Storage and Query Testing

Figure 4 shows the system data collection and transmission test, query a large amount of operational data of mining equipment stored in a relational database, including equipment information, operation logs, and maintenance records, to test the storage capacity and storage speed. Conduct complex SQL query tests on the stored data: When a relational database stores a large number of equipment operation logs, once the data volume exceeds a certain level, the write speed will drop by approximately 20%-60%; the response time of some complex SQL queries exceeds 1 - 2 seconds.

C. Data Application Testing

On the visual interfaces, as shown in Figure 5, we viewed information such as the real - time status of equipment and production reports, and checked the data update frequency and display accuracy. We also tested the integration with the ERP system via the Web API to see if the equipment operation data could be shared and collaborated normally.

The test results showed that there was a delay in data update on the visual interface. The update interval of the real - time equipment status was about 10 seconds, which affected the timeliness of operational decision - making. There were statistical errors in some production report data, so it was necessary to check the data processing logic. When integrating with the ERP system, the sharing of some equipment data failed. It was found that this was due to the problem of data interface permission settings, and it became normal after modification.

x6_borco_Maj...	2544	Engine Speed	800	rpm	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2558	single_drive_dist...	2915	km	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2566	total_drive_dista...	140541	km	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2579	Engine Fuel 1 Te...	38	°C	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2597	can_actual_weight	111	t	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2605	Fuel Level	46	%	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2606	Truck Speed	0	KPH	2024-09-12 09:11:01.000	GOOD	FLOAT32
x6_borco_Maj...	2553	Engine Fuel Rate	12	l/h	2024-09-12 09:10:58.000	GOOD	FLOAT32
x6_borco_Maj...	2543	Engine Speed	800	rpm	2024-09-12 09:10:54.000	GOOD	FLOAT32
x6_borco_Maj...	2556	single_drive_dist...	4150	km	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2564	total_drive_dista...	181097	km	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2601	Fuel Level	59	%	2024-09-12 09:10:54.000	GOOD	FLOAT32
x6_borco_Maj...	2602	Truck Speed	0	KPH	2024-09-12 09:10:54.000	GOOD	FLOAT32
x6_borco_Maj...	2575	Engine Fuel 1 Te...	38	°C	2024-09-12 09:10:54.000	GOOD	FLOAT32
x6_borco_Maj...	2576	Engine Total Ho...	28665	h	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2596	can_actual_weight	0	t	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2611	Engine Total Rev...	2123936000	r	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2552	Engine Fuel Rate	15	l/h	2024-09-12 09:10:50.000	GOOD	FLOAT32
x6_borco_Maj...	2578	Engine Total Ho...	21741	h	2024-09-12 09:10:56.000	GOOD	FLOAT32
x6_borco_Maj...	2612	Engine Total Rev...	1615282944	r	2024-09-12 09:10:56.000	GOOD	FLOAT32
x6_borco_Maj...	2545	Engine Speed	1400	rpm	2024-09-12 09:10:54.000	GOOD	FLOAT32
x6_borco_Maj...	2554	Engine Fuel Rate	40	l/h	2024-09-12 09:10:53.000	GOOD	FLOAT32
x6_borco_Maj...	2581	Engine Total Ho...	27204	h	2024-09-12 09:10:52.000	GOOD	FLOAT32
x6_borco_Maj...	2582	Engine Fuel 1 Te...	39	°C	2024-09-12 09:10:52.000	GOOD	FLOAT32
x6_borco_Maj...	2613	Engine Total Rev...	2027613056	r	2024-09-12 09:10:52.000	GOOD	FLOAT32
x6_borco_Maj...	2555	single_drive_dist...	5889	km	2024-09-12 09:10:50.000	GOOD	FLOAT32
x6_borco_Maj...	2563	total_drive_dista...	176283	km	2024-09-12 09:10:50.000	GOOD	FLOAT32
x6_borco_Maj...	2577	Engine Total Fuel...	2990187	l	2024-09-12 09:10:30.000	GOOD	FLOAT32
x6_borco_Maj...	2590	Engine Trip Fuel	2990062	l	2024-09-12 09:10:30.000	GOOD	FLOAT32
x6_borco_Maj...	2598	can_actual_weight	0	t	2024-09-12 09:10:50.000	GOOD	FLOAT32
x6_borco_Maj...	2599	Fuel Level	83	%	2024-09-12 09:10:49.000	GOOD	FLOAT32
x6_borco_Maj...	2600	Truck Speed	12	KPH	2024-09-12 09:10:49.000	GOOD	FLOAT32
x6_borco_Maj...	3076	Engine Speed	504373984	rpm	2024-09-12 09:10:31.000	GOOD	FLOAT32
x6_borco_Maj...	3081	Fuel Consumptio...	214745104	L/h	2024-09-12 09:10:31.000	GOOD	FLOAT32

Figure 4: System Data Acquisition and Transmission Testing

Figure 5: System Visualization Display Testing

VI. Conclusions

This paper has designed and implemented a cost management system for mobile mining equipment based on the Internet of Things and multi - objective optimization algorithms, and achieved satisfactory results. By combining Internet of Things technology with mobile mining equipment, complex trade - offs among different objectives have been realized, and scientific and reasonable decision - making basis has been provided for decision makers.In conclusion, through the organic integration of Internet of Things technology and multi - objective optimization algorithms, this system has realized the transformation of cost management for mobile mining equipment from traditional single - dimensional optimization to multi - dimensional system - level optimization, providing an innovative and efficient cost management solution for the mining industry.

Acknowledgment

This work was supported in part by the project “Development of a Cost Intelligent Analysis System for Zijin Mining Equipment” under Project No. 20243160A0723, in part by the project “Research and Application of a Mining Production Control Platform Based on IoT and Big Data” under Serial No.20240866, funded by the 2024 Industry-University-Research Collaboration Program of the Longyan Xiamen University Integration Research Institute, and in part by the project “Research and Application of Mine Workers’ Behavior Recognition Based on RFID and Deep Learning,” funded by the Open Research Fund of the State Key Laboratory of Intelligent Manufacturing in Metallurgical Processes (2025).

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