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Research on Modeling Quantum Computing Applications in Mine Equipment Configuration and Operations

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Abstract. This paper explores the optimization of mine equipment configuration and operations using quantum computing and the Quadratic Unconstrained Binary Optimization (QUBO) model. It highlights quantum computing's ability to enhance problem-solving efficiency and solution quality, especially for complex and multivariable optimization problems, compared to traditional methods.The research focuses on two main areas: optimizing equipment configuration and scheduling operations. For equipment configuration, potential schemes are analyzed for complexity and cost-effectiveness, with validation on quantum hardware. For operation scheduling, equipment data is analyzed to create an optimization model, demonstrating improved efficiency through simulations.The study concludes that quantum computing significantly enhances efficiency and solution quality for mine equipment management, proving its superiority over traditional methods.

Keywords: Quantum, Computing, Configuration, Operations, QUBO Model.

1. Introduction

As the global economy and resource demand continue to grow, traditional mining techniques have become insufficient to meet the needs for modern efficiency, low cost, and environmental sustainability.Thus, the exploration of advanced technological solutions has become imperative, particularly in leveraging emerging technologies to optimize mining equipment configuration and operations [1]. Quantum computing, with its potential for extraordinary computational power, is seen as a key to solving complex optimization problems [2]. The application of quantum computing in the optimization of mining equipment configuration and operations is of significant importance. Firstly, it can validate the advantages of quantum computing in addressing complex system problems, providing practical case studies. Secondly, this aids in the transition of quantum computing from theory to practice, laying the foundation for its commercialization. Finally, optimizing mining equipment configuration and operational strategies can enhance production efficiency, reduce costs, and achieve both economic and environmental benefits, thereby promoting the modernization and sustainable development of the mining industry. With the advancement of quantum computers, quantum optimization algorithms, particularly quantum annealing and the Quantum Approximate Optimization Algorithm (QAOA) [3], have shown potential in addressing NP-hard problems. This paper explores the applicability of these algorithms to executing QUBO models, effectively utilizing the superposition and entanglement properties of quantum states to enable rapid exploration of complex search spaces.

2. A Study on Simple Optimization Problems in Mining Equipment Configuration and Operations

This study assumes that, in order to simplify the complexity of management and scheduling and to reduce the risk of safety incidents caused by changes in matching, the pairing between excavators and mining trucks is fixed and unchanging. It is assumed that excavators of the same model can only be paired with mining trucks of the same model, and only the procurement costs of excavators incurred in the first year are considered.

2.1. Preparation of the Model

2.1.1. QUBO Model

The QUBO model, which stands for Quadratic Unconstrained Binary Optimization, is commonly used for modeling combinatorial optimization problems1. The basic form of the QUBO model is as follows:

$$\mathrm{Min} \sum_{x_i, x_j \in \wedge, i \neq j} \beta_{ij} x_i x_j + \sum_{x_i \in \wedge} \alpha_i x_i \tag{1}$$

Let x_i and x_j be binary variables (0-1 variables), and let $\wedge = \{x_1, x_2, ..., x_N\}$ be the set of binary variables, where Nis the number of binary variables. β_{ij} represents the quadratic term coefficients in the QUBO model, and α_i represents the linear term coefficients in the QUBO model.

Since the quadratic form of a binary variable x_i is equivalent to its linear form $x_i = x_i^2$, the QUBO model can also be expressed in matrix form as follows:

$$\mathrm{Min}\, X^T Q X \tag{2}$$

Where $X = [x_1, x_2, ..., x_N]^T$;Qis the coefficient matrix of the QUBO model, and the symmetric form of Q is given by $Q_{ii} = \alpha_i$ and $Q_{ij} = \beta_{ij} / 2$.

2.1.2. Quantum Computing

Quantum computing utilizes the principles of quantum mechanics to process information. With quantum superposition and entanglement, it exhibits superior computational capabilities. Compared to Ising models, Coherent Ising Machines (CIMs) are optical quantum computers that can solve QUBO or optimization problems in quantum computing. Quantum annealing is a notable optimization algorithm within quantum computing [4].

2.2. Model Construction

A QUBO model is required, utilizing quantum annealers and CIM solvers to address the procurement scheme with maximum long-term profits within the defined computation scope. This problem is converted into a quadratic optimization problem to establish the QUBO model [5].First, binary variables are defined to represent each excavation machine, where $x_i = 1$ indicates selection for procurement and $x_i = 0$ indicates rejection. Integer variables n_i represent the number of machines procured, and L_i represents the long-term profit present value of the excavation machine. The initial objective function can be expressed as:

$$\text{Maximize} \quad Z = \sum_{i=1}^{4} x_i \cdot n_i \cdot L_i \tag{3}$$

2.2.1. Type Constraint

$$x_1 + x_2 + x_3 + x_4 \geq 3 \tag{4}$$

Transform the QUBO problem's constraint from equation (4) by setting a large penalty factor P. If this constraint is violated, add it to the objective function:

$$P \cdot (3 - (x_1 + x_2 + x_3 + x_4))^2 \tag{5}$$

2.2.2. Budget Constraint

$$\sum_{i=1}^{4} x_i \cdot n_i \cdot C_i \leq 2400 \tag{6}$$

Here, C_i represents the purchase price of the excavator i .Set a large penalty factor Q.If this constraint is violated, add it to the objective function:

$$Q \cdot \max(0, \sum_{i=1}^{4} x_i \cdot n_i \cdot C_i - 2400))^2 \tag{7}$$

Incorporate all the above objective and constraint conditions. The updated objective function is:

$$\text{Max} \quad Z = \sum_{i=1}^{4} x_i \cdot n_i \cdot L_i - P \cdot (3 - (x_1 + x_2 + x_3 + x_4))^2 - Q \cdot \max(0, \sum_{i=1}^{4} x_i \cdot n_i \cdot C_i - 2400))^2 \tag{8}$$

2.3. Model Solution

From the results presented in Table 1, it can be concluded that selecting 1 unit of Excavator Model 1, 2 units of Excavator Model 2, 10 units of Excavator Model 3, and 0 units of Excavator Model 4 achieves the maximum profit of 580 million yuan within the budget.

Table 1. Solution Results.

Result	Excavator 1 = 1 unit; Excavator 2 = 2 units; Excavator 3 = 10 units
Profit	58000 million yuan
Total Cost	23.8 million yuan

With the increase in budget, the number of Excavator 4s has significantly increased, while the numbers of Excavators 1, 2, and 3 have remained relatively stable.According to fig.1, the distribution of the excavator model quantities is as follows:

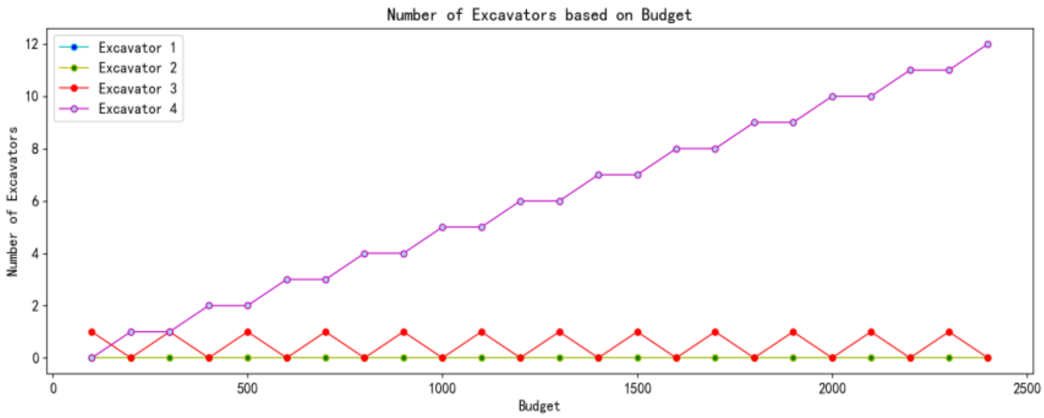

Figure 1. Results of Excavator Model Quantities.

The horizontal axis represents the budget, and the vertical axis represents the profit. The curve in the graph indicates a linear relationship between profit and budget; as the budget increases, the profit correspondingly increases. The data points in the graph form a straight line with a consistent slope, demonstrating that for each increment in budget, the profit increases at a constant rate.As shown in fig.2, the profit maximization results are illustrated.

Figure 2. Profit Maximization Results.

2.3.1. Solution via Simulated Annealing Algorithm

The simulated annealing algorithm mimics the physical annealing process [6].It generates initial solutions randomly in the search space and accepts worse solutions through the control of temperature parameters, thus avoiding local optima and reaching the global optimum. The simulated annealing algorithm parameters are set as follows: the initial temperature is 100, the cooling rate is 0.99, and the stopping criterion is 100 iterations. Below is the graph showing the cost variation with the number of iterations obtained from the simulated annealing process,As shown in Figure 3:

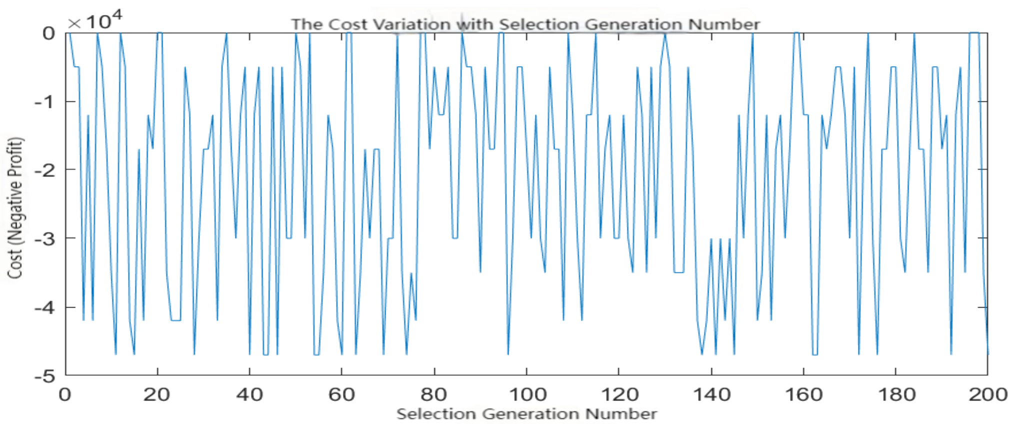

Figure 3. Cost Variation with Number of Iterations.

Finally, the optimal solution obtained by the simulated annealing solver is shown in the spatial location in fig.4:

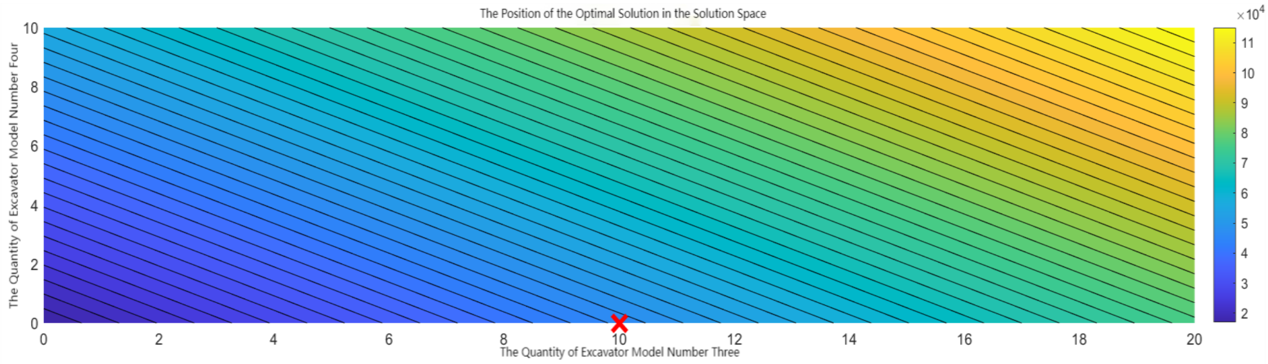

Figure 4. Optimal Solution in Spatial Position.

2.3.2. CIM Simulator Solution

By inputting the CIM-Ising matrix, setting the pump power to 0.7, noise intensity to 0.01, the number of cycles to 1000, and the cycle step length to 0.1, the simulated quantum bit evolution is obtained, as shown in fig.5:

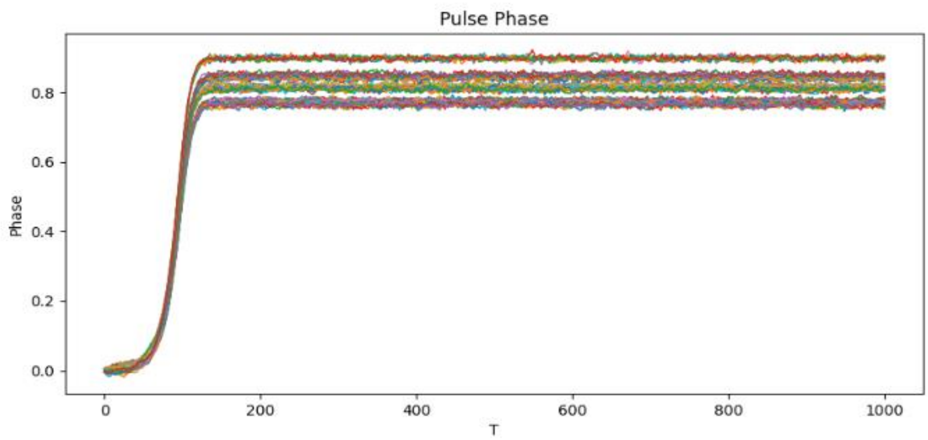

Figure 5. Quantum Bit Evolution.

The obtained Hamiltonian is shown in fig.6:

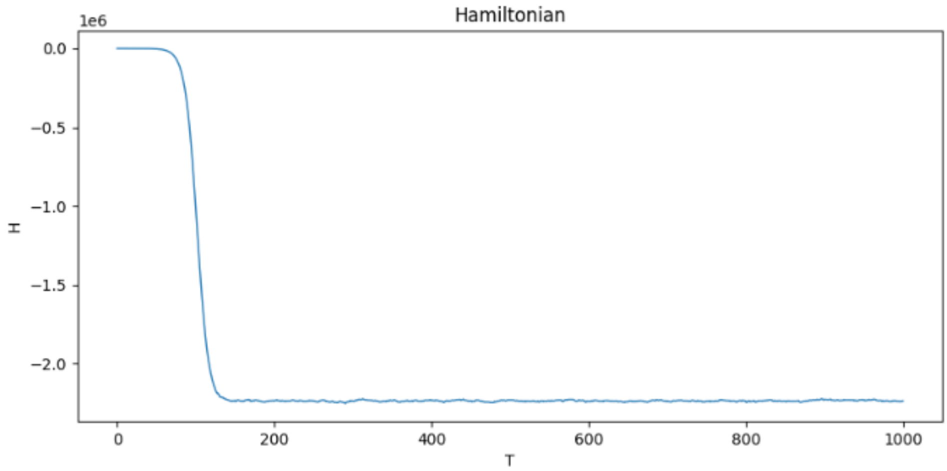

Figure 6. Hamiltonian.

Using the CIM simulator, laser pulses in optical fibers are used as quantum bits for computation. By finding the state with the lowest energy, the optimal solution of this paper is obtained [7]. The profit maximization result of this paper is shown in fig.7:

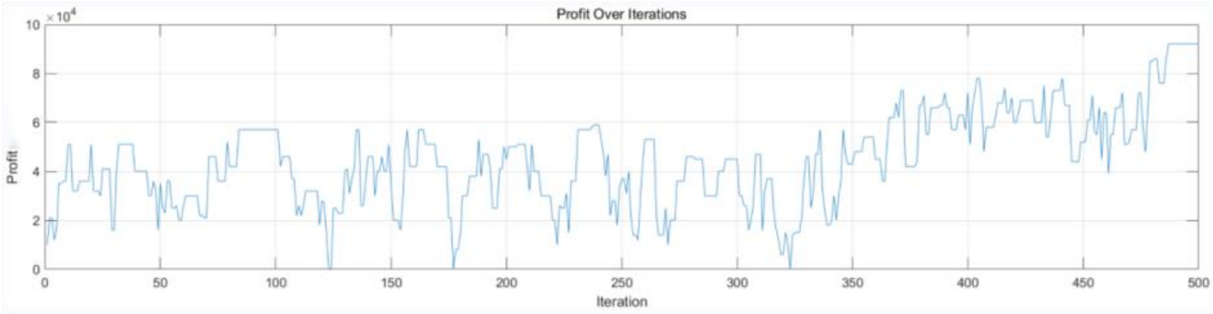

Figure 7. Profit Results.

3. Under certain conditions, research on simple optimization problems in the configuration and operation of mining equipment

3.1. Model Preparation

Similar to traditional simulated annealing, quantum annealing is prone to tunneling effects. While simulated annealing requires overcoming large energy barriers to find the global minimum, quantum annealing can exploit tunneling to easily reach the global minimum [8]. The tunneling probability is influenced by the potential field and the width of the energy barrier, as shown in fig.8.

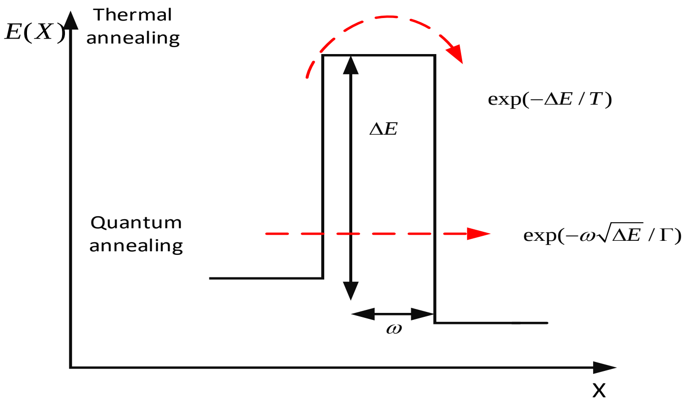

Figure 8. Comparison between Simulated Annealing and Quantum Annealing in Terms of Energy Barriers.

Quantum annealing can outperform simulated annealing in optimization problems by leveraging tunneling effects. Simulated annealing requires gradually overcoming the highest energy barriers to reach the global minimum, whereas quantum annealing can directly tunnel through barriers, as illustrated in fig.9.

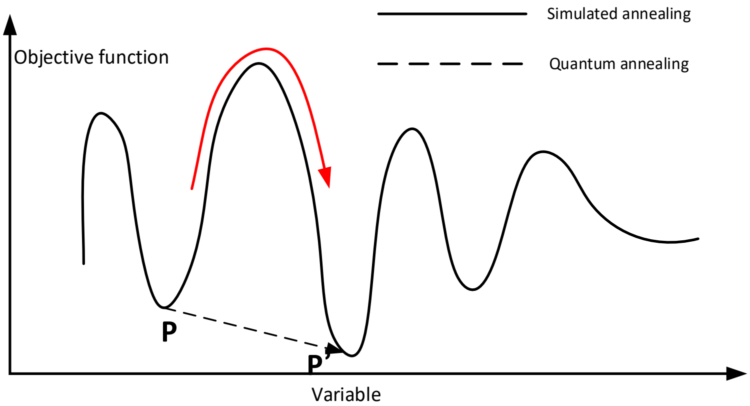

Figure 9. Working Principle Comparison between Simulated Annealing and Quantum Annealing.

3.2. Model Construction

This study establishes a QUBO model, utilizing a simulated annealer and a CIM model solver to address the optimization problem of maximizing excavator profitability while considering the matching problem with dump trucks [9].

3.2.1. Objective Function:

Let x_i represent the purchase decision variable for excavator i (1 indicates purchase, 0 indicates no purchase).Let n_i be the number of excavators purchased, and V_i the long-term profit value of excavator i The objective function can be expressed as:

$$\text{Maximize } \sum_{i=1}^{N} V_i \times x_i \times n_i \tag{9}$$

3.2.2. Type Matching Constraint:

Each excavator's matching condition with a dump truck is represented by a binary variable C_{ij} ,where i denotes the type of excavator and j denotes the type of dump truck. If excavator i matches with truck j ,then $C_{ij}=1$;otherwise, $C_{ij}=0$ .The type matching constraint is incorporated into the objective function through a penalty term P ,which is defined as:

$$P \times \sum_{i=1}^{N} \sum_{j=1}^{M} (1-C_{ij}) \times x_i \times y_j \tag{10}$$

3.2.3. Budget Constraint:

The budget constraint ensures that the total purchase cost does not exceed the budget B.Let B_i be the purchase price of excavator i .The penalty term for violating the budget constraint is defined as:

$$Q \times \left(\sum_{i=1}^{N} B_i \times x_i \times n_i - B\right)^2 \tag{11}$$

Where Q is a large penalty factor to enforce the budget constraint.

Incorporating both constraints, the objective function for the QUBO model is:

$$\text{Max } \left(\sum_{i=1}^{N} V_i \times x_i \times n_i\right) - P \times \sum_{i=1}^{N} \sum_{j=1}^{M} (1-C_{ij}) \times x_i \times y_j - Q \times \left(\sum_{i=1}^{N} B_i \times x_i \times n_i - B\right)^2 \tag{12}$$

Here, $x_i \in \{0,1\}$ is the purchase decision variable for excavator i , $y_j \in \{0,1\}$ is the purchase decision variable for truck j , V_i is the long-term profit value of excavator i , C_{ij} represents the matching condition, B_i is the purchase price, and B is the budget.

3.3. Model Solution

Solving the model yields the selection of 7 units of excavator type 1, 3 units of excavator type 3, 1 unit of excavator type 2, and 2 units of excavator type 2 under the given conditions to maximize the total profit.

The data is summarized and presented in Tables 2 and 3.

Table 2. Parameters for Four Types of Excavators.

Type	Bucket Capacity(m^3)	Operation Efficiency (h)	Fuel Consumption (L/h)	Purchase Price (¥)	Labor Cost (¥)	Maintenance Cost (¥)
1	0.9	190	28	100	7000	1000
2	1.2	175	30	140	7500	1500
3	1.8	165	34	200	8500	2000
4	2.1	150	38	320	9000	3000

Table 3. Parameters for Three Types of Dump Trucks.

Type	Fuel Consumption (L/h)	Labor Cost (¥/month)	Maintenance Cost (¥/month)	Monthly Working Hours (h)	Fuel Price (¥/L)	Stone Price (¥/m^3)	Truck Limit (units)
1	18	6000	2000	160	7	20	7
2	22	7000	3000				7
3	27	8000	4000				3

Maximizing total profit over five years without considering the matching relationship between excavators and mining trucks. Based on Scenario 1, the relationship is added, resulting in the data shown in Table 4.

Table 4. Cost Calculation in Scenario 1.

Type	Quantity	Purchase Cost (¥)	Fuel Cost (¥)	Labor Cost (¥)	Maintenance Cost (¥)	Total Cost (¥)
Excavator1	7	70000	13171200	2940000	420000	16601200
Excavator2	3	42000	6048000	1350000	270000	7710000
Excavator3	1	20000	2284800	510000	120000	2934800
Excavator4	2	64000	5107200	1080000	360000	6611200
1	7	/	8467200	2520000	840000	11827200
2	3	/	4435200	1260000	540000	6235200
3	1	/	1814400	480000	240000	2534400

3.3.1. Solving with Simulated Annealing Solver

Set the objective function, initial solution, initial temperature, annealing rate, number of iterations, and other parameters [10]. Utilize the simulated annealing solver to find the optimal solution, as shown in fig.10:

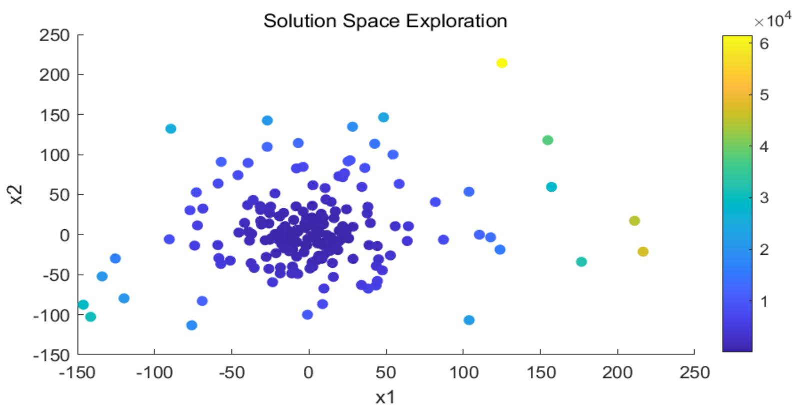

Figure 10. Solution Space Exploration of Simulated Annealing Solver.

By employing the simulated annealing solver, the paper find that the optimal solution includes 7 units of excavator type 1, 5 units of excavator type 2, 4 units of excavator type 3, and no units of excavator type 4, as shown in Figures 10 and 11.

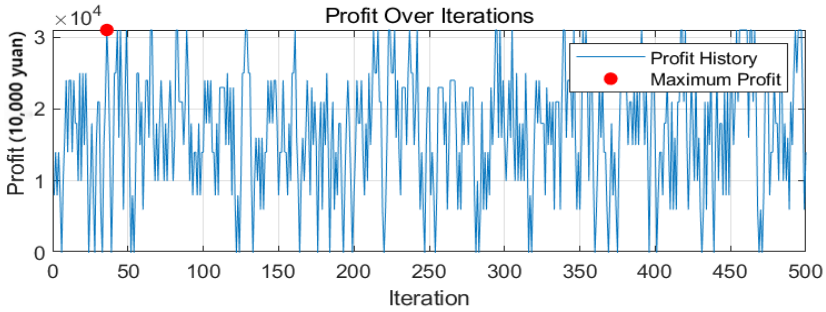

Figure 11. Profit Variation Over Iterations.

3.3.2. Solving with CIM Solver

Set the appropriate parameters and utilize the Kaiwu SDK's kaiwu.cim module to solve for the total profit maximization. The process and results are illustrated in Figures 12 and 13.

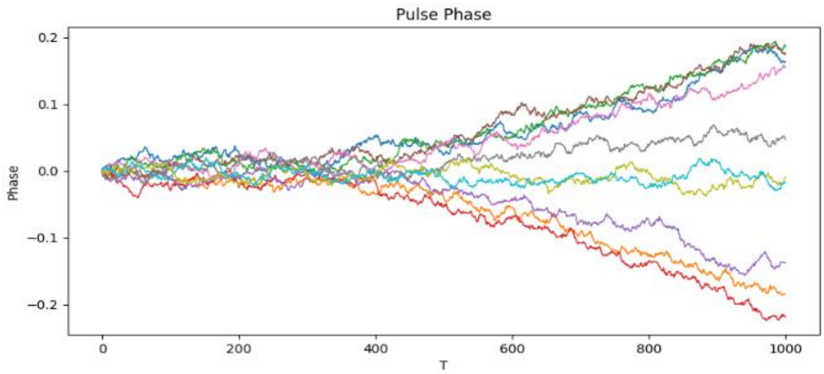

Figure 12. Quantum Bit Annealing Process.

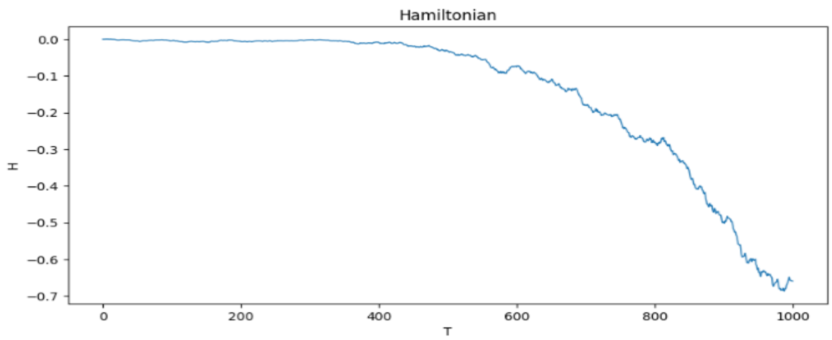

Figure 13. Quantum Bit Annealing Process.

By using the CIM solver with the appropriate parameters set, the paper obtained the results shown in fig.14:

Figure 14. Profit Variation over Iterations with CIM Solver.

4. Conclusion

This paper makes several significant contributions to the field of mine equipment configuration and operations management. First, it demonstrates the practical application of quantum computing, specifically the Quadratic Unconstrained Binary Optimization (QUBO) model, in optimizing complex mining operations. Second, it establishes a methodology for integrating quantum computing with traditional optimization techniques, highlighting the superior performance of quantum methods in terms of speed and accuracy. Lastly, the study provides valuable insights into the cost-benefit analysis and efficiency metrics, thereby promoting the modernization and sustainable development of the mining industry.

The feasibility of this research is evidenced by the successful implementation and validation of the QUBO model on quantum computing hardware. The study effectively simplifies the complexities involved in mine equipment configuration and operations, ensuring that the model is both practical and adaptable to real-world scenarios. By addressing key factors such as matching relationships between excavators and dump trucks, as well as budget constraints, the model outputs reliable and accurate results. This approach ensures that the proposed solutions are not only theoretically sound but also practically viable, thereby maximizing operational efficiency and profitability within the mining sector.

References

[1] The People's Republic of China and the Fourteenth Five-Year Plan for National Economic and Social Development and the 2035 Vision Goals Outline [N]. People's Daily, 2021-03-13(001).

[2] Yuan Ye, Xu Hao, Wang Xi. Traffic Docking of City Subway Transfer in Public Transport Network Based on Quantum Computer [J/OL]. Urban Rail Transit, 2024: 1-7.

[3] Wang Baonan, Shui Henghua, Wang Suming, et al. Quantum Fire Theory and Its Application Summary [J]. Chinese Science: Physics, Mechanics, Astronomy, 2021, 51(08): 5-17.

[4] Du Welin, Li Bin, Tian Yu. Development Progress of Quantum Fire Theory Research [J]. Computer Research and Development, 2008, 09(09): 1501-1508.

[5] Liu Zhimei. Deep Integration of Mathematical Modeling and High Vocational Mathematics Teaching [J]. Jiasida Business College Journal, 2023, 39(03): 152-154.

[6] Chen Peng. Python-Based Modeling and Simulation of Bullet Ejection Optimization Scheme [J]. New Industrialization, 2022, 12(12): 289-293.

[7] Xie Yujing, Han Huili. Multidimensional Analysis of Digital Model Construction in Primary Mathematics Textbooks of Beijing Normal University Press [J]. Educational Management, 2023, 09(09): 73-76.

[8] Li Zhanbo, Wu Wencheng, Li Shuyan, et al. Role of Inner Mongolia's Sanda Wusu River Basin Graphite Mine in Formation of Quartz Sandstone [J]. Chinese Geology, 2022, 49(04): 1009-1047.

[9] Wang Baonan, Yao Haonan, Hu Feng, et al. Distributed Exact Solution Study on Quantum Fire Ising Model with Partial Field Parameters h and Coupling Parameters J [J]. Chinese Science: Physics, Mechanics, Astronomy, 2020, 50(03): 131-146.

[10] Guo Mengjie, Wang Han, Yan Zheng, et al. Optimization Method of Distributed Resource Aggregation for Virtual Power Plant Based on Photonic Quantum Computer [J/OL]. Chinese Computer Engineering, 2024: 1-12.