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Article

Research on Optimized Mine Equipment Configuration Using an Improved QUBO Model

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Abstract: The intelligent mine has successfully attained the objective of cost reduction and efficiency enhancement, hence optimizing corporate advantages, through the implementation of a complete information system for mine safety production that facilitates connectivity among users at all hierarchical levels and diverse roles. Challenges such as unbalanced equipment layout and suboptimal efficiency have emerged as impediments to the advancement of intelligent mining operations. This scholarly paper presents a novel objective function that seeks to optimize earnings over a span of five years. The objective function incorporates binary 0-1 decision variables and auxiliary variables. The last step involves the establishment of many constraints, such as the stipulation for a minimum of three distinct excavators, limitations on the values assigned to decision and auxiliary variables, and restrictions on the quantities of each excav model. In conclusion, the utilization of the Kaiwu SDK in the simulated annealing solver yielded a viable solution for mining equipment, thereby offering a coherent strategy for the advancement of intelligent mining operations and the arrangement of mining equipment.

Keywords: Equipment Configuration; Maximum Profit;0-1 Variables; QUBO Model

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1. Introduction

The evolution of coal mining has undergone distinct phases, inclusive of manual mining, mechanized mining, and automated mining. At now, there is a notable progression towards the use of safe and environmentally sustainable intelligent mining practices. During the course of this development, several concerns have emerged, including inappropriate allocation of equipment, suboptimal mining efficiency, and an imbalanced correlation between investment and output. A study conducted by Zhou[1] et al. examined the significance of equipment allocation in the context of large-scale mine production operations. A study conducted by Nong Dehai et al. involved the computation of the total cost of ownership (TCO) in order to ascertain the most advantageous equipment distribution strategy. Nevertheless, the majority of these models exhibit computational complexity, time-intensive processes, and necessitate substantial storage capacity, hence impeding the advancement of intelligent mining.

In view of its distinct benefits in the computation and simulation of intricate systems, the advancement of quantum computing[2] possesses substantial scientific and societal significance. It assumes a pivotal role in domains such as machine learning and operations research, whereby conventional computer methodologies encounter difficulties. The Quadratic Unconstrained Binary Optimization (QUBO) model[3]-**错误!未找到引用源。** is one of the most commonly employed simulation models in quantum computing. The predominant approach to mining equipment allocation study relies on conventional optimization models, which are characterized by their sluggishness and complexity in solving problems. In order to overcome the limits inherent in conventional models and facilitate the progress of intelligent mining, this study introduces a quadratic constrained maximization model that takes into account diverse real-world constraints. Subsequently, this model is converted into a QUBO model. A supplementary variable with a range of 0-1 is incorporated into the conventional QUBO model in order to enhance computational efficiency and render the outcomes more useful in practical applications. The primary contributions of this study are outlined as follows:

1) This paper presents a pragmatic analysis of a mining development dilemma.

2) Developing a comprehensive multi-objective (QUBO) model.

3) The incorporation of an additional 0-1 variable into the conventional QUBO model represents a potential enhancement.

2. Problem Modeling

2.1 Problem Statement

A intelligent mine company that is about to start operations has an initial capital of 24 million yuan and plans to operate for five years. A comprehensive equipment configuration and operation plan needs to be designed, considering seven factors: excavator bucket capacity, excavator operating efficiency, mining truck loading capacity, fuel consumption, price, labor cost, and maintenance cost. Based on these factors, the plan should determine the models and quantities of excavators to be purchased and establish the matching relationship between excavators and mining trucks to maximize total profit over five years.

Four types of excavators are available, with equipment parameters shown in Table 1. Three types of mining trucks have already been purchased, with quantities of 7, 7, and 3 respectively, and their parameters are shown in Table 2. Both excavators and mining trucks are assumed to work 20 days a month, 8 hours a day, with a fuel price of 7 yuan per liter and an ore price of 20 yuan per cubic meter.

Table 1. Parameters of Four Excavators

Model	Bucket Capacity	Operating Efficiency	Fuel Consumption	Purchase Price	Labor Cost	Maintenance Cost
Excavator1	0.9	190	28	100	7000	1000
Excavator2	1.2	175	30	140	7500	1500
Excavator3	1.8	165	34	200	8500	2000
Excavator4	2.1	150	38	320	9000	3000

Table 2. Parameters of Three Types of Mining Trucks

Model	Fuel Consumption	Labor Cost	Maintenance Cost
Mining Truck1	18	6000	2000
Mining Truck2	22	7000	3000
Mining Truck2	27	8000	4000

In the final configuration plan, the following constraints need to be considered:

1. Given the materials and efficiency of the excavators and mining trucks, large excavators cannot be matched with very small mining trucks, and small excavators will not be matched with very large mining trucks. The matching relationships between different models of excavators and mining trucks are shown in Table 3.

Table 3. Matching Relationships Between Excavators and Mining Trucks

	Mining Truck 1	Mining Truck 2	Mining Truck 3
Excavator1	1	\	\
Excavator2	2	1	\
Excavator3	2	2	1
Excavator4	\	2	1

Note: For example, for Excavator 2, at least two Mining Trucks 1 or one Mining Truck 2 are required to ensure stable operation.

2. In the actual operation of the mine, small excavators are needed for maintenance tasks such as road repair, platform construction, and handling edge materials. At the same time, to ensure overall operational efficiency, a certain number of large excavators are required. This can be summarized as the total number of excavator models must not be less than three.

The efficiency during the operation of the intelligent mine system is calculated according to the following rules:

1. If the matching relationship between excavators and mining trucks exactly equals or exceeds the values in the table, the daily output is based on the efficiency of the excavator.

2. If the number of mining trucks allocated to an excavator is less, the excavator may spend some time waiting for trucks. In this case, the daily output of the excavator is the efficiency multiplied by the corresponding ratio. For example, if an excavator is ideally matched with 2 trucks but is only assigned 1 truck, the excavator's daily output will be half of its standard output.

2.2 QUBO Model Principle

The QUBO[6] model is an optimization model widely used in fields such as combinatorial optimization, signal processing, and quantum computing. The basic mathematical form of the QUBO model is as follows:

$$\min \sum_{x_i,x_j\in\theta,i\neq j} \beta_{ij}x_ix_j + \sum_{x_i\in\theta} \alpha_i x_i \tag{1}$$

where, x_i and x_j be binary 0-1 variables, and θ be the set of binary 0-1 variables, $\theta=\{x_1, x_2, ..., x_n\}$, where n is the number of 0-1 variables. β_{ij} represents the coefficients of the quadratic terms in the above model, and α_i represents the coefficients of the linear terms in the model.

Additionally, due to the special nature of binary 0-1 variables, where $x_i=x_i^2$, the QUBO model can be expressed in matrix form as follows:

$$\min X^TQX \tag{2}$$

$X=\{x_1,x_2,...,x_n\}^T$; Q is the coefficient matrix of the QUBO model,In the symmetric case, $Q_{ii}=\alpha_i$, $Q_{ij}=Q_{ji}=\frac{\beta_{ij}}{2}$, $i\neq j$.

2.3 Ising Model Principle

The Ising[7] model is a type of random process model used to describe phase transitions in materials. In the field of quantum computing, this model is commonly used to describe the interactions between quantum bits and their coupling relationships. It is a common tool in quantum computing for solving optimization problems. The decision variables in the Ising problem take values in $\{-1,1\}$. The objective function contains N variables $s=[s_1,\ldots,s_n]$, where $s_i\in\{-1,1\}$.

In general, a QUBO problem can be equivalently represented using the Ising model. By transforming the variables using $x_i\rightarrow(I+\sigma_i)/2$, the original QUBO model's decision variable domain $\{0,1\}$ is mapped to the Ising model's decision variable domain $\{-1,1\}$. The transformation process and the resulting objective function in the Ising problem are expressed as follows:

$$J_{ij}=\frac{1}{4}Q_{ij},h_i=-\frac{1}{2}\left(c_i+\sum_{j\in X}Q_{ij}\right) \tag{3}$$

$$\min \sum_{(i,j)\in E} J_{ij y_i y_j} + \sum_{i\in x} h_i y_i \tag{4}$$

where, J and h are the quadratic and linear coefficients of the Ising model, respectively, with $y_i \in \{-1,1\}$, $i \in X=[1,2,3\ldots\ldots,N]$. By using the Ising model combined with methods such as quantum annealing, the optimal solution to the objective function can be obtained.

2.4 Symbol Description

Due to the use of numerous variables in this paper, the explanations for some important variables are provided in Table 4.

Table 4. Variable Descriptions

Symbol	Description
u_{ij}	Whether to purchase j units of Excavator Model i
y_{ik}	Whether Excavator Model i is matched with Mining Truck j
q_i	Bucket capacity of Excavator Model i, $q_i \in Q$
w_i	Standard operating efficiency of Excavator Model i, $w_i \in W$
p_i	Purchase price of Excavator Model i, $p_i \in P$
r_i	Fuel consumption of Excavator Model i, $r_i \in R$
h_i	Labor cost of Excavator Model i, $h_i \in H$
s_i	Maintenance cost of Excavator Model i, $s_i \in S$
t_m	Fuel consumption of Mining Truck Model m, $t_m \in T$
d_m	Labor cost of Mining Truck Model m, $d_m \in D$
v_m	Maintenance cost of Mining Truck Model m, $v_m \in V$
f_m	Number of Mining Truck Model m, $f_m \in F$
β_{ij}	Standard quantity of Mining Truck Model j matched with Excavator Model i
Funding	Initial startup capital

2.5 Construction of the Objective Function

According to the problem statement, the goal is to maximize the total profit over 5 years, considering the models and quantities of purchased excavators and the matching relationships between excavators and mining trucks. The profit calculation formula is:

$$\text{Profit=Revenue-Various Costs} \tag{5}$$

Based on the problem context, the cost calculation formula is:

$$\text{Cost=Excavator Cost+Mining Truck Cost} \tag{6}$$

Where the cost for each excavator and mining truck is calculated as follows:

$$\text{Excavator Cost=Purchase+Fuel+Labor Cost+Maintenance Cost} \tag{7}$$

$$\text{Mining TruckCost=Fuel Consumption+LaborCost+Maintenance Cost} \tag{8}$$

The formula for daily revenue is:

$$\text{Daily Revenue=Quantity}\times\text{Bucket Capacity}\times\text{Efficiency}\times 8\times 20 \tag{9}$$

Therefore, the formula for revenue over five years is:

$$\text{Revenue=E\_Capacity}\times\text{S\_Efficiency}\times 8\times 20\times 20\times 12\times 5+\text{Capital} \tag{10}$$

E_Capacity stands for Excavator Bucket Capacity; S_Efficiency stands for Standard Efficiency

It is noted that if the actual number of matched mining trucks exceeds the standard quantity, the efficiency of the excavator remains unchanged. If it is less than the standard quantity, the efficiency of the excavator will vary according to the number of matched mining trucks. Therefore, this paper introduces a weight α to modify the revenue calculation formula. The final formula for revenue over five years is:

$$\text{Revenue}=\text{E\_Capacity}\times\text{A\_ Efficiency}\times 8\times 20\times 20\times 12\times 5+\text{Capital} \tag{11}$$

A_ Efficiency stands for Actual Efficiency;

Where the actual efficiency is calculated using:

$$\text{A\_Efficiency}=\alpha\times\text{S\_Efficiency} \tag{12}$$

$$\alpha=\frac{\text{Actual Number of Matched Mining Trucks}}{\text{Standard Number of Matched Trucks}},\alpha\in(0,1) \tag{13}$$

Note: When the actual number of matched mining trucks $\geq$ standard number of matched trucks, $\alpha=1$.

Let C represent various costs, q_i be the bucket capacity of Excavator Model i, w_i be the standard operating efficiency, p_i be the purchase price, r_i be the fuel consumption, h_i be the labor cost, s_i be the maintenance cost of Excavator Model i, t_m be the fuel consumption, d_m be the labor cost, v_m be the maintenance cost, and f_m be the number of Mining Truck Model mmm. Introduce the binary 0-1 variable:

$$u_{ij}=\begin{cases}0, & \text{No purchase of j units of Excavator Model i,}\\ 1, & \text{purchase of j units of Excavator Model i.}\end{cases}$$

Due to the limitations on the number of mining trucks, and without considering costs, the maximum number of excavators of each model that can be purchased, given the matching table and reasonable resource allocation, is shown in Table 5.

Table 5: Maximum Purchase Quantities for Each Excavator Model

Model	Quantity
Excavator 1	7
Excavator 2	7
Excavator 3	4
Excavator 4	4

where, the set is $i\in\{1,2,3,4\}$, $j\in\{1,2,...,7\}$.

In the traditional QUBO model, there is only one binary 0-1 variable, which makes it difficult to represent and solve complex problems. Therefore, this paper introduces an additional auxiliary binary 0-1 variable y_{ik} to improve the traditional QUBO model, in addition to the existing u_{ij}.

$$y_{ik}=\begin{cases}0,\text{Excavator Model i does not match with Mining Truck numbered k,}\\ 1,\text{Excavator Model i matches with Mining Truck numbered k.}\end{cases}$$

Mining trucks are numbered sequentially from Mining Truck 1 to Mining Truck 3, with the numbering set $K=\{1,2,3,...,1\}$. $k_{1\text{-}7}$ are the numbers for Mining Truck Model 1, $k_{8\text{-}14}$

are for Mining Truck Model 2, and $k_{15\text{-}17}$ are for Mining Truck Model 3. The variable y_{ik} has certain constraints: if $y_{12}=1$, then $y_{11}=1$; if $y_{11}=1$, y_{12} can be either 0 or 1.

Thus, the mathematical expressions for various costs are derived from equations (11), (12), and (13) as follows:

$$C=\sum_{i=1}^{4}\sum_{j=1}^{7} ju_{ij}\,p_i+\sum_{i=1}^{4}\sum_{j=1}^{7} ju_{ij}(r_i\times 7\times 8\times 20+h_i+s_i)\times 12\times 5+\sum_{m=1}^{3} f_m(t_m\times 8\times 20+d_m+v_m)\times 12\times 5 \tag{14}$$

The mathematical expression for the total revenue is as follows:

$$M=\left(\sum_{i=1}^{4}\sum_{j=1}^{7} ju_{ij}q_i\alpha w_i\times 20\times 8\times 20\times 12\times 5\right)+\text{Funding} \tag{15}$$

$$\alpha=\frac{\sum_{k=1}^{17} y_{ik}}{\beta_{ij}},i\in\{1,2,3,4\} \tag{16}$$

Let M be the revenue, Funding be the initial capital, and β_{ij} be the standard number of Mining Trucks Model j matched with Excavator Model i. Due to the nature of the decision variables, we have $u_{ij}=u_{ij}^2$.

$$\text{Max}\left(\sum_{i=1}^{4}\sum_{j=1}^{7} 192000ju_{ij}^2q_i\alpha w_i\right)+\text{Funding-}$$
$$\left(\sum_{i=1}^{4}\sum_{j=1}^{7} ju_{ij}^2\,p_i+\sum_{i=1}^{4}\sum_{j=1}^{7} ju_{ij}^2(1120r_i+h_i+s_i)\times 60+\sum_{m=1}^{3} f_m(160t_m+d_m+v_m)\times 60\right) \tag{17}$$

2.6 Construction of Constraint Conditions

Based on the problem context and the limitations of variable values, the following five constraints must be satisfied:

(1) There must be at least three types of excavators.

(2) Constraints on the values of u_{ij} variables.

(3) Limits on the quantity of each type of excavator.

(4) The total number of mining trucks matched with all excavators must not exceed the available number of mining trucks.

(5) Constraints on the types of mining trucks that each type of excavator can match.

According to the problem statement, to avoid the impact of various unexpected situations on mining operations, the number of excavator types must be at least three. Therefore, the first constraint established to limit the number of excavator types is as follows:

$$\sum_{i=1}^{4}\sum_{j=1}^{7} u_{ij}\geq 3 \tag{18}$$

Here, a slack variable a_2 is introduced to transform the inequality constraint into an equality, as follows:

$$\sum_{i=1}^{4}\sum_{j=1}^{7}u_{ij}-a_2=3 \tag{19}$$

Considering the meaning of the binary 0-1 variable u_{ij}, the second constraint based on the limitations of u_{ij} values is as follows:

$$\sum_{j=1}^{7}u_{ij}\leq 1, i\in\{1,2,3,4\} \tag{20}$$

Based on Table 5, it can be seen that Excavator Models 3 and 4 can each be purchased up to four units without considering costs.

1） Quantity Limitation for Excavator Model 3

$$\sum_{j=5}^{7}u_{3j}=0 \tag{21}$$

2） Quantity Limitation for Excavator Model 4

$$\sum_{j=5}^{7}u_{4j}=0 \tag{22}$$

Based on equations (17) and (18), the third constraint condition established for the quantity limits of each type of excavator is as follows:

$$\sum_{i=3}^{4}\sum_{j=5}^{7}u_{ij}=0 \tag{23}$$

Due to the limited number of mining trucks, the total number of mining trucks matched with all excavators cannot exceed the available number of mining trucks. The fourth constraint condition based on the number of mining trucks is as follows:

1） Constraint on the number of Mining Truck Model 1

$$\sum_{i=1}^{4}\sum_{k=1}^{7}y_{ik}=7 \tag{24}$$

2） Constraint on the number of Mining Truck Model 2

$$\sum_{i=1}^{4}\sum_{k=8}^{14}y_{ik}=7 \tag{25}$$

3） Constraint on the number of Mining Truck Model 3

$$\sum_{i=1}^{4}\sum_{k=15}^{17}y_{ik}=3 \tag{26}$$

Considering the rationality of resource allocation, large excavators cannot be matched with small mining trucks and small excavators cannot be matched with large mining trucks. Therefore, the fifth constraint condition, based on the given standard excavator-to-mining truck matching table, is as follows:

1） Constraint on the types of mining trucks matched with Excavator Model 1

$$\sum_{k=8}^{17} y_{1k} = 0 \tag{27}$$

The constraints on the values of y_{1k} are as follows:

$$y_{1(k+1)} \leq y_{1k}, k \in \{1,2,...,7\} \tag{28}$$

Based on equations (27) and (28), the constraint on the types of mining trucks matched with Excavator Model 1 is as follows:

$$y_{1(k+1)} \leq y_{1k}, k \in \{1,2,...,7\} \tag{29}$$

$$y_{18} = 0, i = 1,\ k = 8 \tag{30}$$

The constraint principle for Excavator Model 2 is the same as above.

2）Constraint on the types of mining trucks matched with Excavator Model 2

$$y_{2(k+1)} \leq y_{2k}, k \in \{1,2,...,14\} \tag{31}$$

$$y_{215} = 0, i = 2,\ k = 15 \tag{32}$$

3）Constraint on the types of mining trucks matched with Excavator Model 3

There are no type constraints for Excavator Model 3, so Excavator Model 3 only has constraints on the values of the y_{ik} variable.

$$y_{3(k+1)} \leq y_{3k}, k \in K \tag{33}$$

4）Constraint on the types of mining trucks matched with Excavator Model 4

$$\sum_{k=1}^{7} y_{2k} = 0 \tag{34}$$

$$y_{4(k+1)} \leq y_{4k}, k \in \{8,9,...,17\} \tag{35}$$

5）Constraint on the matching relationship between each excavator and mining truck

$$\sum_{i=1}^{4} y_{ik} \leq 1, k \in K \tag{36}$$

The corresponding values for some variables are as follows:

$q_i=[0.9,1.2,1.8,2.1], w_i=[190,175,165,150]$,

$r_i=[28,30,34,38], p_i=[100,140,200,320]$,

$h_i=[7000,7500,8500,9000], s_i=[1000,1500,2000,3000]$,

$t_m=[18,22,27], d_m=[6000,7000,8000]$,

$v_m=[2000,3000,4000], f_m=[7,7,3]$.

According to the common constraint conversion[8] table shown in Table 6, the above quadratic constrained binary optimization model can be rewritten as a quadratic unconstrained binary optimization (QUBO) model by adding a penalty term PPP, as shown in Equation (37).

Table 6. Common Constraint Conversion Table

Classical Constraint	Equivalent Penalty
$x + y \leq 1$	$P(xy)$
$x + y \geq 1$	$P(1 - x - y - xy)$
$x + y = 1$	$P(1 - x - y - 2xy)$
$x \leq y$	$P(x - xy)$
$x_1 + x_2 + x_3 \leq 1$	$P(x_1x_2 + x_1x_3 + x_2x_3)$
$x = y$	$P(x + y - xy)$

$$\begin{aligned}\min\ & -\left(\sum_{i=1}^{4}\sum_{j=1}^{7} 192000 j u_{ij}{}^{2} q_i \alpha w_i\right) + D - \left(\sum_{i=1}^{4}\sum_{j=1}^{7} j u_{ij}{}^{2} p_i + \sum_{i=1}^{4}\sum_{j=1}^{7} j u_{ij}{}^{2}(1120 r_i + h_i + s_i)\times 60 + \sum_{m=1}^{3} f_m(160 t_m + d_m + v_m)\times 60\right) \\ & + P\left(\sum_{i=1}^{4}\sum_{j=1}^{7} u_{ij} - a_2 - 3\right)^2 + P\left(\prod_{j=1}^{7} u_{ij}\right)^2 + P\left(\sum_{i=1}^{4}\sum_{k=1}^{7} y_{ik} - 7\right)^2 + P\left(\sum_{i=1}^{4}\sum_{k=8}^{14} y_{ik} - 7\right)^2 + P\left(\sum_{i=1}^{4}\sum_{k=15}^{17} y_{ik} - 3\right)^2 \\ & + P\left(\sum_{i=1}^{4}\sum_{k=15}^{17} y_{ik} - 3\right)^2 + P\left(y_{1(k+1)} - y_{1(k+1)} y_{1k}\right)^2 + P\left(y_{2(k+1)} - y_{2(k+1)} y_{2k}\right)^2 + P\left(y_{3(k+1)} - y_{3(k+1)} y_{3k}\right)^2 + \\ & P\left(y_{4(k+1)} - y_{4(k+1)} y_{4k}\right)^2 + P(y_{18})^2 + P(y_{215})^2 + P\left(\sum_{k=1}^{7} y_{2k}\right)^2 + P\left(\sum_{i=3}^{4}\sum_{j=5}^{7} u_{ij}\right)^2 + P\left(\prod_{i=1}^{4} y_{ik}\right)^2 \end{aligned} \quad (37)$$

3. Results

The objective function is further simplified to the following form:

$$\min\ -X^{T}QX$$

where $X = (u_{11}, u_{12}, \ldots\ldots u_{47}, y_1, y_2 \ldots\ldots y_{17}, a_2)_{43}$ is a 43-dimensional vector, and QQQ is the QUBO coefficient matrix, shaped as a (43,43) matrix. The QUBO model is converted to an Ising model and solved using the simulated annealing solver built into Kaiwu SDK on the Boson Quantum Platform (https://developer.qboson.com/login) to obtain the optimal decision variables X and auxiliary variables Y.

Finally, after calculation, setting $P=10000$, the excavator purchasing schemes obtained using the Kaiwu SDK simulated annealing solver are shown in Tables 7 and 8.

Table 7. Excavator Purchasing Scheme Obtained from the Simulated Annealing Solver

Model	Quantity
Excavator 1	7
Excavator 2	1
Excavator 3	3
Excavator 4	3

Table 8: Excavator-to-Mining Truck Matching Relationship Obtained from the Simulated Annealing Solver

	Mining Truck 1	**Mining Truck 2**	**Mining Truck 3**
Excavator 1	7	\	\
Excavator 2	0	1	\
Excavator 3	0	2	0
Excavator 4	\	0	1

The final matching relationships between the mining trucks and excavators, as well as the corresponding quantities of each excavator model, can be derived from Tables 7 and 8.

4. Discussion

This paper utilizes the QUBO model to address the configuration problem of mining equipment, aiming to maximize the mining benefits for the company. By introducing two binary 0-1 variables, the traditional QUBO model has been improved to enhance its practicality. Using the 0-1 variables u_{ij} and y_{ik} as decision variables to represent the quantity relationships of excavators and the matching relationships between excavators and mining trucks respectively, with the objective of profit maximization as the objective function, and constraints including the limitation of matching relationships and variable values, the QUBO model for mining equipment configuration was established based on the optimized model for mining truck equipment configuration. The research results indicate that when solving the QUBO model, attention needs to be focused only on the Q matrix, which simplifies the computation, provides good solutions, and achieves fast solving speeds. Overall, the improved QUBO model is easier to establish and solve compared to traditional optimization and QUBO models, and it provides effective solutions for mining equipment configuration. The computational complexity and time required for the QUBO model are significantly lower than those of traditional optimization models. This indicates that the QUBO model outperforms traditional optimization models in terms of effectiveness.

5. Conclusions

In the end, the enhanced QUBO model exhibits a straightforward framework for establishment and resolution, thereby offering a proficient resolution for the allocation of mining equipment. In addition to its application in mining equipment, the QUBO model may also be extended to alternative domains, including offshore resource allocation, personnel scheduling, and logistics distribution. In the forthcoming study, the QUBO model will be utilized to investigate route optimization in logistics distribution and devise an enhanced solving algorithm, thereby making a valuable contribution to the progress of quantum computing.

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