Analysis of Mining Equipment Procurement Plan and Logistics Path Optimization Based on QUBO Model

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ABSTRACT

By analyzing the configuration and operation plan of mining equipment, this paper establishes a linear programming model and converts it into the corresponding quadratic unconstrained binary optimization (QUBO) form. Based on this, the simulated annealing solver built-in in Kaiwu SDK and CIM simulator are used to study the configuration and operation plan of mining equipment. It is required to provide a procurement plan that maximizes profits within the budget range, that is, to determine the required excavator models and corresponding quantities. This problem is based on the premise of not considering the service life of excavators, with the maximum value of the product of the four excavator models and their corresponding long-term profits and quantities as the objective function, and with the constraints of start-up capital budget and excavator type, a 0-1 integer programming model is established. By using the decision variable of the model as a 0-1 variable and the constraint as an inequality constraint, the constraint is then transformed into the corresponding Hamiltonian operator, and the penalty term coefficient P is introduced and added to the objective function, thereby transforming it into QUBO form. Due to the low complexity and linearity of the model, the Kaiwu SDK's built-in simulated annealing solver and CIM simulator were used to solve the problem and obtain the final maximum profit and procurement plan.

Keywords: 0-1 Integer Programming; QUBO Model; Simulated Annealing Solver; CIM Simulator

1 INTRODUCTION

With the rapid development of intelligent technology, traditional mining methods have become inadequate and unable to meet the needs of modernization, efficiency, and safety [1]. Smart mining, as an innovative concept in the modern mining industry, is gradually emerging and continuously receiving widespread attention and recognition from the industry [2]. Therefore, major equipment suppliers have followed the trend of the times and actively transformed into service providers providing overall solutions for smart mines, in order to highlight their core competitiveness and market position in the industry and adapt to the new trend of mining development [3]. The construction of smart mines relies heavily on advanced information technology and equipment automation, making it a complex and systematic project [4]. By integrating cutting-edge technologies, smart mines can achieve comprehensive monitoring and optimization of the mining process, thereby improving mining efficiency, reducing resource energy consumption, reducing environmental pollution, effectively reducing mining accidents, ensuring the safety of miners, and ultimately achieving true green and intelligent mining [5].

In the actual operation of smart mines, in order to ensure efficient, safe, and economical operational results, it is necessary to accurately configure equipment and design operational plans based on specific conditions of the mine, such as workload, model capacity, operational efficiency, fuel consumption, purchase price, and labor costs [6]. Especially for the procurement, allocation, and use of key resources such as excavators and mining trucks, strict planning and decision-making are required to ensure the maximum utilization of resources and the overall efficiency of mining [7]. It can be seen that smart mining has become an important trend in the development of modern mining [8]. In the process of providing overall solutions for smart mines, equipment suppliers need to scientifically and reasonably design and optimize equipment configuration and operation plans based on the specific needs of the mine, which directly determines their position and success in market competition, and thus stand out in market competition [9].

Based on the given estimated discounted profit value, without considering the service life of the excavator, establish a QUBO model, use CIM simulation and Kaiwu SDK simulation annealing to solve for the procurement plan that maximizes the total profit within the budget rang.

2 WORK ANALYSIS AND ASSUMPTION

The core of work one lies in determining the model and quantity of excavators reasonably based on the given long-term profit discount table, in order to maximize overall revenue within a limited budget. To complete this task, it is necessary to first construct an appropriate mathematical model, and then further transform it into QUBO form for solving. As the title already provides long-term profit data for each excavator, our focus will be on cost control and model selection. Therefore, this article plans to construct an optimization constraint model. The key to this model lies in constructing a reasonable objective function and setting appropriate constraints. After completing these steps, convert the model into QUBO form to adapt to the subsequent solving process [10].

It is worth noting that the constraints include specific forms of the QUBO model, such as $X1 + X2 + X3 \leq 1$. This feature can directly incorporate inequality constraints as penalty terms into the objective function, thereby simplifying the solving process of the model. In terms of solving, the work clearly requires the use of the Kaiwu SDK's built-in simulated annealing solver and CIM simulator [11]. These two methods have their own advantages, and through their combined use, more accurate and reliable procurement plans can be obtained, and the optimization effect of the plans can be comprehensively evaluated.

3 MODEL BUILDING AND ANALYSIS

Quadratic unconstrained optimization problem is an important optimization problem, which is widely used in many fields, such as machine learning, signal processing, control theory and so on. The main characteristic of this kind of problem is that the objective function is a quadratic function, and there is no explicit constraint [12]. The quadratic unconstrained optimization problem has a relatively simple form in mathematics, so its theoretical properties are relatively clear. The property of quadratic function makes its optimization problem have definite analytical solution, that is, the optimal solution can be found by derivation and solving the equation. This makes the quadratic unconstrained optimization problem very important in both theoretical analysis and practical application.

Quadratic unconstrained optimization problems are widely used in practical applications. For example, in machine learning, many loss functions are quadratic, such as the mean square error loss function. In signal processing, the quadratic unconstrained optimization problem can be used to estimate the minimum mean square error of a signal. In control theory, quadratic unconstrained optimization problems can be used to solve the optimal control strategy. The quadratic unconstrained optimization problem has important theoretical and application value. Through in-depth research and application, it can promote the development of related fields and improve the effect and efficiency of practical application.

3.1 Building a constrained optimization model

According to the obtained data and target requirements, the linear programming model is designed to meet the requirements. The model should be developed in order to fully take into account the various constraints on the production line, such as the limited resources and the urgency of time. The goal of the model is to achieve optimization by increasing production efficiency, reducing costs, or improving product quality. A linear programming model can be expressed in the following form:

Objective function:

$$Z = c_1x_1 + c_2x_2 + \cdots + c_nx_n \tag{1}$$

Constraints:

$$min\ c^T x \tag{2}$$

$$s.t.\left\{\begin{matrix} Ax \le b \\ Aeq \cdot x = beq \\ lb \le x \le ub \end{matrix}\right\} \tag{3}$$

Where, c and x are n dimensional column vectors, A and Aeq are matrices of appropriate dimension, and b and beq are column vectors of appropriate dimension.

The standard form of a general linear programming problem is

$$\max z = \sum_{j=1}^{n} C_j X_j \tag{4}$$

$$s.t.\left\{\sum_{j=1}^{n} a_{ij} X_i = b_i\right\}\ i = 1,2,\cdots,m;\ j = 1,2,\cdots,m \tag{5}$$

Where, $x_1, x_2, \cdots, x_n$ are the decision variable, $b_1, b_2, \cdots, b_n$ are the right-hand constant of the constraint condition.

The goal of a linear programming model is to find the values of a set of decision variables so that the objective function can obtain the maximum or minimum value while satisfying all the constraints.

Table 1: Raw data of long-term profits

Model number	Type 1	Type 2	Type 3	Type 4
Discount the present value of long-term profits	2000	3000	5000	6000

Based on the raw data in Table 1, which provides discounted present value estimates of the long-term profits brought by each type of excavator, the total revenue can be calculated directly using these data. Specifically, total revenue can be obtained by the following formula:

$$Total\ revenue\ = \sum the\ present\ value\ of\ the\ longterm\ profits\ of\ various\ excavators$$
$$x\ the\ \ number\ of\ various\ excavators) \tag{6}$$

Here you need to multiply the present value of the long-term profits of each type of excavator by its number, and add all the results together to arrive at the total expected revenue.

(1) Objective function: total profit:

$$Max\ Z_1 = 2000xX_1 + 3000xX_2 + 5000xX_3 + 6000xX_4 \tag{7}$$

(2) Constraints:

$$X_1 \geq y_1;\ X_2 \geq y_2;\ X_3 \geq y_3;\ y_1{+}y_2{+}y_3 \geq 3 \tag{8}$$

$$y_1, y_2, y_3 \in (0\ ,1) \tag{9}$$

$$100xX_1 + 140xX_2 + 200xX_3 + 320xX_4 \leq 2400 \tag{10}$$

By taking these factors into account, we can build a more comprehensive and accurate optimization constraint model to support the decision-making process.

3.2 Building a QUBO model

The traditional constrained optimization model can be transformed into a quadratic unconstrained optimization model by using QUBO model to solve the problem. By constructing constraint conditions, the constraint conditions are put into the objective function, the constraint terms are added, and a large enough penalty coefficient P is introduced to ensure that the constraint is satisfied. Finally, the QUBO model formula of problem 1 solution model can be obtained as follows:

$$Max\ Z_2 = 100xX_1 + 140xX_2 + 200xX_3 + 320xX_4 + P(X_1xX_2 + X_1xX_3 + X_2xX_3) \tag{11}$$

3.3 Model solving and analysis

Simulated Annealing (SA) algorithm can effectively solve Quadratic Unconstrained Binary Optimization (QUBO) problem. QUBO problem is a kind of binary optimization problem, the goal is to minimize a polynomial function containing only quadratic and first terms between variables. For simulated annealing algorithm to solve QUBO model, given a QUBO problem, the form is:

$$E(x) = \sum_{i=1}^{n} Q_{ij}\, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} Q_{ij}\, x_i x_j \tag{12}$$

Where, $x = (x_1, x_2, \cdots, x_n)$ is a binary vector, $x_2 \in (0,1)$. $Q = (Q_{ij})$ is a symmetric n by n matrix representing QUBO coefficients.

CIM is a method that utilizes quantum or quantum heuristics to solve Optimization problems, especially for the Ising model or QUBO (Quadratic Unconstrained Binary Optimization). The model is solved using the solver built into the Kaiwu SDK, following the following steps:

(1) Define the problem: Transform the traditional optimization problem into QUBO form. It is difficult to convert the nonlinear constraint into soft constraint by introducing the penalty term P, so that the value of the objective function increases.

(2) Write code: Use the API or interface provided by the SDK to write code. For the simulated annealing solver, the following parameters need to be set:

Initial temperature T_0: The initial simulation temperature to accept larger perturbations at the beginning of the search;

Termination temperature T_{min}: When the temperature drops to the threshold value, the iteration stops;

Cooling rate α : control the proportion of temperature drop at each step, the value is within (0,1);

MaxIter: Set the maximum number of iterations as a stop condition to prevent the algorithm from infinite loops;

Initial solution x_0: Introduce a binary vector as the initial solution.

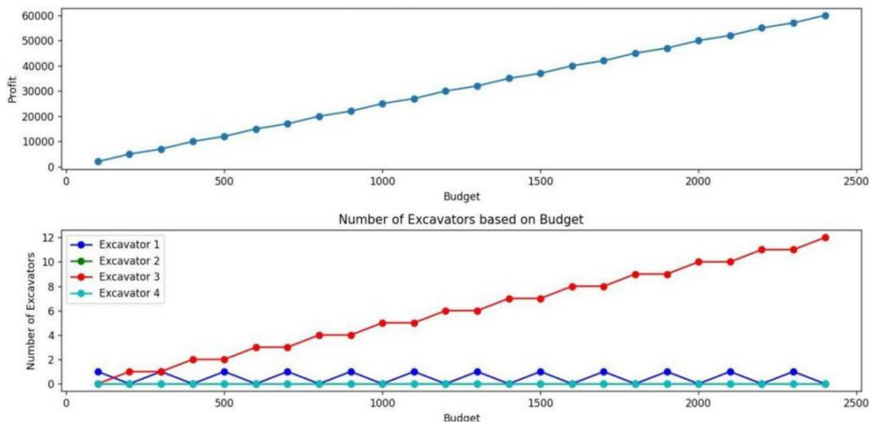

Fig.1: Dynamic distribution of budget solved by simulated annealing algorithm

Through the analysis of the dynamic distribution table in Figure 1, it can be seen that excavator 4 was eliminated from the data competition at the very beginning due to the fact that the requirements of various indicators did not meet the requirements, so the final procurement plan only considered the first three items, and then obtained the priority purchase of excavator 3 through continuous iteration through MaxIter.

(3) Solver operation: Input the QUBO problem into the solver and start the solving process. For simulated annealing, the solver will gradually reduce the temperature according to the plan, while searching for the best solution; For CIM simulator, it seeks the optimal solution by simulating the evolution of quantum system. After the solver is run, an optimal solution or multiple candidate solutions will be obtained. By evaluating the quality of the solutions, the final procurement plan of the excavator is obtained as shown in Table 2.

Table 2: Procurement options

Type 1	Type 2	Type 3	Type 4	Maximum profit (ten thousand yuan)
1	2	10	0	58000

4 CONCLUSIONS

In terms of solving efficiency, methods for solving the QUBO model have been extensively studied and developed. Various solving methods, including classical heuristic algorithms, quantum algorithms, etc., can to some extent ensure the efficiency and quality of the solution. This makes the QUBO model highly competitive in practical applications and able to quickly find the optimal solution to the problem. Linear programming has the advantages of simple and intuitive modeling, efficient and reliable solution, wide application range, optimized resource allocation, assisted decision-making, and promoting sustainable development. These advantages make linear programming a very important decision-making tool, with significant value in solving various practical problems. With the continuous development of science and technology and the expansion of application fields, linear programming will play a more important role in the future.

The quadratic constraint optimization model is a mathematical optimization model widely used in various practical problems, which involves finding a set of variables that satisfy a series of quadratic constraint conditions while achieving the optimal value of a certain quadratic objective function. The quadratic constraint optimization model can handle a large number of practical problems, such as portfolio optimization, production planning, logistics optimization, etc. In addition, the model can flexibly handle various forms of constraint conditions, including linear, quadratic, and more complex nonlinear constraints. The following are the main advantages of quadratic constraint models:

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