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A Cost-effective Pump Scheduling Method for Mine Drainage System Based on Ant Colony Optimization

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ABSTRACT

With pumps as the main devices, the main drainage system (MDS) is critical to mine construction and production. Considering the high cost of traditional manual pump scheduling strategy and the wide adoption of time-of-use (TOU) electricity traffic in coal mines, this paper attempts to reduce the mine operation cost by scheduling the pumps in the flat and valley periods instead of the peak period. For this purpose, the pump scheduling was considered as an optimization problem, the water level of the sump was predicted by double exponential smoothing, and then the optimal pump scheduling plan was derived by ant colony optimization (ACO). The pump scheduling plan obtained by the proposed method was proved cost efficient through experiments on a gold mine in China.

1. INTRODUCTION

The mine drainage system (MDS) prevents groundwater and surface water from leaking into the mine during mine construction and production, providing an important guarantee of mine safety against water damage [1]. Most MDSs are controlled manually, i.e. turned on or off by an operator based on his/her experience. The manual control mode consumes lots of electricity. In Chinese coal mining enterprises, the MDSs account for 40 % of the power consumption by all electromechanical devices in coal mines [2-3]. Since the pump is the centerpiece of each MDS, it is important to design a pump scheduling algorithm to save energy and reduce the relevant cost.

Many pump scheduling methods are available to water distribution systems (WDSs). However, these approaches cannot be applied directly to the MDSs, owing to the following differences between the WDSs and MDSs [4]: the water flow is stable in the WDSs but constantly changing in MDSs; the urban water demand has basically the same daily variation [5], while the mine water inflow mutates from time to time.

To solve the problem, this paper proposes a cost-effective pump scheduling (CEPS) algorithm based on water inflow prediction and ant colony optimization (ACO). The main contributions of this paper incudes are as follows: treating the pump scheduling in the MDSs as a discrete optimization problem; developing a water inflow prediction method based on double exponential smoothing to guide the pump scheduling; creating an ACO-based algorithm to obtain the most cost-effective pump schedule.

The remainder of this paper is organized as follows: Section 2 reviews the previous studies on pump scheduling; Section 3 formulates the pump scheduling problem; Section 4 details the CEPS algorithm; Section 5 applies the CEPS into an actual case of pump scheduling and analyzes the results; Section 6 wraps up this paper with some conclusions

2. LITERATURE REVIEW

Pump scheduling is an emerging hotspot in the research of the WDSs, whose water supply relies heavily on pump stations. The pump scheduling of the WDSs is generally treated as an optimization problem, and solved by different optimization algorithms to obtain the (sub)optimal solution. For example, Reference [5] reduces the energy and maintenance costs of WDS pump scheduling by two meta-heuristics, simulated annealing (SA) and hybrid genetic algorithm (HGA), and experimentally proves that the SA outperforms the HGA. Reference [6] considers the joint problem of pump scheduling and water flow control as a mixed-integer second-order cone program, and solves the program with the alternating direction method of multiplier. Reference [7] creates a mixed-integer linear programming model for the scheduling of variable-speed pumps in hydropower stations. Reference [8] models the scheduling of multiple water-lifting pumps in China's South-to-North Water Diversion Project, which aims to solve the water shortage in northern China, as an optimal operation problem, and solves the problem through dynamic programming. Reference [9] puts forward a similar solution to Mahasawat water distribution station in Thailand. All these energy-saving strategies provide good references to the pump scheduling of the MDSs. However, special algorithms should be designed for the MDSs, owing to the said differences between the WDSs and MDSs.

Some of the representative studies on pump scheduling of the MDSs are reviewed as follows. Reference [10] presents a variable-speed hybrid Petri net model of the MDS, and creates on online pump control algorithm based on the model, but the model is difficult to establish due to the MDS variation from mine to mine. Targeting the coal seam 14# in China's Linnancang Coalmine, Reference [11] sets up a comprehensive model of the seepage field to determine the proper water level in adjacent aquifers, and optimizes the main drainage capacity using the finite-element subsurface flow system. To improve pump efficiency in the MDSs, Reference [12] establishes a model based on the HGA, but fails to consider the change law of water level. Reference [13] constructs a multi-pump MDSs optimization model, and applies the artificial bee colony algorithm to determine the number of running pumps in different periods. Reference [14] develops a gray correlation model between water inflow and time, as well as an economic MDS model to implement the load shifting schedule. Based on the water inflow of China's Fuxin Coalmine, Reference [15] provides a dynamic gray model, and designs an automatic, energy-efficient EDS control system. To sum up, the above models all consider MDSs pump scheduling as a continuous optimization problem, which may lead to fragmentation of pump running time. The frequent start and stop of pumps will exacerbate equipment aging. Therefore, this paper views the pump scheduling as a discrete optimization problem, aiming to strike a balance between the number of pump starts/stops and the electricity consumption.

3. PROBLEM FORMULATION

Table 1 lists the main symbols and their definitions in this paper. A typical MDS consists of a water sump to store the mineral water, and several pumps to drain the water from the sump when the water level surpasses the pre-set threshold. Because the electricity consumption varies from period to period in one day, the power supply usually adopts the time-of-use (TOU) electricity tariff mechanism to minimize the pressure on the grid. As shown in Figure 1, the TOU electricity tariff divides one day (24 hours) into several periods, and the electricity tariff in each period may falls into the valley, flat or peak segment. In this case, the pump scheduling is to determine the pump running period that minimizes the electricity consumption and control the water level in the sump under the pre-set threshold.

Table 1. Symbols and definitions

Symbol	Definition
H_t	Water level at time t
ϕ	The predefined threshold of water level
K	Number of pumps of an MDS
p	Power of a pump
L	Length of predefined time period (unit: minute)
N	Number of time periods in 24 hours, $L \cdot N =$ 1440 minutes
C	Cost of pumps in 1 day
c_p, c_f, c_v	Electricity tariff in peak, flat, and valley segment, respectively
n_s	Number of running pumps in sth period, $0 \leq s \leq N$
c_s	Electricity tariff in sth period
H_s	Water level at the beginning of sth period
F_s	Increased water level by water inflow in sth period
D_s	Decreased water level by draining water with pumps in sth period
$F_s^{(1)}$	Basic exponential smoothing value of F_s
$F_s^{(2)}$	Double exponential smoothing value of F_s
$\hat{H}_s$	Predicted value of H_s
d	Decreased water level by one pump in one time period
ω	Smoothing factor to compute $F_s^{(1)}$ and $F_s^{(2)}$
$G = (V, E, W)$	Multistage directed and weighted graph for pump schedule
$v_j^{(s)} \in V$	A vertex of G, which is in sth stage
$v_s^{(0)}, v_e^{(N+1)} \in V$	Additional first and last vertex of G
V_s	Set of vertices of sth stage
$w_{i,j}$	Weight of edge $\langle v_i^{(s)}, v_j^{(s+1)} \rangle$
M	Number of ants of ACO
$\tau_{i,j}$	Pheromone laying on edge $\langle v_i^{(s)}, v_j^{(s+1)} \rangle$
$\eta_{i,j}$	Locally available heuristic information of edge $\langle v_i^{(s)}, v_j^{(s+1)} \rangle$
$\rho_{i,j}^A$	Probability of ant A at $v_i^{(s)}$ to choose $v_j^{(s+1)}$ to visit
C_{best}	Cost of the best pump schedule
α, β, ρ	Parameters used in ACO
$ItrMax$	Maximum number of iterations of ACO

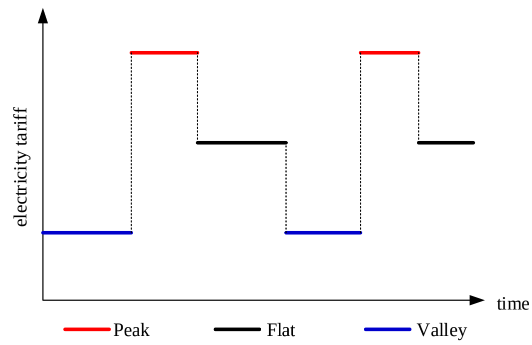

Figure 1. The TOU electricity tariff

Let H_t be the water level of the sump at time t, ϕ be the pre-set threshold of water level, and K be the number of pumps of an MDS. Meanwhile, it is assumed that the pumps have the same, nonadjustable power p, each day (24 hours) encompasses N periods of equal length L and the same electricity tariff, and the electricity tariffs in peak, flat, and valley segments are c_p, c_f and c_v, respectively. Then, the daily pump cost of the MDS can be expressed as:

$$C = \sum_{i=1}^{K} \int_0^{24} \big(p \cdot r(t) \cdot c(t)\big) dt \tag{1}$$

where $r(t) = 0$ if the pump is off at time t, and $r(t) = 1$ if the pump is on at time t; $c(t)$ is the electricity tariff at time t. Since each day is divided into several periods, equation (1) can be transformed into:

$$C = \sum_{s=1}^{N} p \cdot n_s \cdot c_s \cdot L \tag{2}$$

where n_s and c_s are the number of running pumps and electricity tariff in period s, respectively. Therefore, the pump scheduling problem can be defined as:

$$\begin{gathered} \min C = \sum_{s=1}^{N} p \cdot n_s \cdot c_s \cdot L \\ s.t. \\ 0 \leq n_s \leq K \\ c_s \in \{c_p, c_f, c_v\} \\ 0 \leq H_t \leq \phi \end{gathered} \tag{3}$$

If the water level of the sump is predictable, then the problem defined in equation (3) is to find the n_s at the beginning of each period, such that the solution space contains

$(K+1)^N$ feasible solutions. This task is hard to solve by brute force. This paper adopts the ACO to complete the task. The ACO provides a desirable way to solve discrete optimization problems [15]. This algorithm is inspired by the behavior of real ant colonies: when an ant colony wants to find the shortest path between their nest and a food source, the ants constantly release pheromones, directing each other to resources, while exploring their environment. Each ant constructs a feasible solution and updates the pheromones according to the quality of solution, and the pheromones guide the ants to construct a better solution in the next loop.

4. CEPS DESIGN

4.1 Water level prediction

As mentioned before, each day can be divided into several periods of equal length; in each period, each pump is either in the on state or the off state. Hence, it is necessary to determine the water level at the beginning of each period. Let H_s be the water level at the beginning of period s. Then, the water level at the subsequent period can be calculated as:

$$\mathrm{H_{s+1} = H_s + F_s - D_s} \tag{4}$$

where F_s is the water level increase induced by the water inflow; D_s is the water level decrease induced by the water drainage. The value of D_s is already known, as the pump parameters are given in advance. The pumps should be turned on if H_{s+1} is greater than the pre-set threshold on water level ϕ. Since the F_s is constantly changing, the double exponential smoothing was introduced to predict its value.

Let ω be the smoothing factor. Then, the basic exponential smoothing value of the F_s can be described as:

$$\mathrm{F_{s+1}^{(1)} = \omega F_s + (1-\omega) F_s^{(1)}} \tag{5}$$

The double exponential smoothing value of the F_s can be described as:

$$\mathrm{F_{s+1}^{(2)} = \omega F_{s+1}^{(1)} + (1-\omega) F_s^{(2)}} \tag{6}$$

Then, the predicted value of F_{s+j} can be obtained as:

$$\hat{F}_{s+j} = a_s + b_s j \tag{7}$$

where

$$\begin{cases} a_s = 2F_s^{(1)} - F_s^{(2)} \\ b_s = \frac{\omega}{1-\omega}\left(F_s^{(1)} - F_s^{(2)}\right) \end{cases} \tag{8}$$

The value of D_s depends on the number of running pumps n_s and the water level reduction d caused by one pump in each period:

$$D_s = n_s d \tag{9}$$

Therefore, the predicted value of $\hat{H}_{s+1}$ can be written as:

$$\mathrm{\hat{H}_{s+1} = H_s + \hat{F}_s - n_s d} \tag{10}$$

4.2 ACO-based pump scheduling

Before solving the pump scheduling problem by the ACO, the problem defined in equation (3) must be transformed into the shortest path problem in a graph.

As shown in Figure 2, the pump scheduling problem can be transformed into a multi-stage directed and weighted graph $\mathrm{G = (V, E, W)}$, where $\mathrm{V} = \left\{v_j^{(s)} \middle| s = 1,2,\cdots,N;\ j = 0,1,\cdots,K.\right\} \cup \left\{v_s^{(0)}, v_e^{(N+1)}\right\}$, $\mathrm{E} = \left\{\langle v_i^{(s)}, v_j^{(s+1)}\rangle\right\} \cup \left\{\langle v_s^{(0)}, v_i^{(1)}\rangle\right\} \cup \left\{\langle v_i^{(N)}, v_e^{(N+1)}\rangle\right\}$ and $\mathrm{W: E \to \mathbb{R}}$ is the weight of edges ($\mathbb{R}$ is the set of real numbers).

Each period corresponds to one stage in G, and each stage has K vertices corresponding to the K pumps. Let $\mathrm{V}_s (i = 1,2,\cdots,N)$ be the set of vertices in stage s. Then, $\mathrm{V}_s = \left\{v_i^{(s)} \middle| i = 0,1,\cdots,K\right\}$. The weight of $\langle v_i^{(s)}, v_j^{(s+1)}\rangle$, $w_{i,j}$, is the cost incurred by turning on j pumps and turning off i pumps, with $w_{s,i} = w_{i,e} = 0\ (i = 1,2,\cdots,K)$. Therefore, the pump scheduling problem is equivalent to finding the shortest path from $v_s^{(0)}$ to $v_e^{(N+1)}$, which can be solved by the ACO.

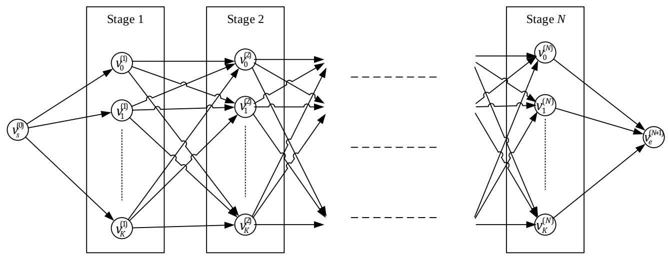

Figure 2. The graph of the pump scheduling problem

The basic procedure of the ACO-based pump scheduling plan is as follows:

Step 1: Solution construction. Initially, M ants are all placed at $v_s^{(0)}$. In each iteration, each ant chooses the next vertex at a certain probability. For ant A at vertex $v_i^{(s)}$, the probability of the ant to visit $v_j^{(s+1)}$ can be expressed as:

$$\rho_{\mathrm{i,j}}^{\mathrm{A}} = \frac{\tau_{\mathrm{i,j}}^{\alpha} \eta_{\mathrm{i,j}}^{\beta}}{\sum_{\mathrm{j=0}}^{\mathrm{K}} \tau_{\mathrm{i,j}}^{\alpha} \eta_{\mathrm{i,j}}^{\beta}} \tag{11}$$

where $\tau_{i,j}$ and $\eta_{i,j} = \frac{1}{w_{i,j}}$ are the pheromone and local heuristic information of $\langle v_i^{(s)}, v_j^{(s+1)}\rangle$, respectively; α and β are the relative importance parameters of $\tau_{i,j}$ and $\eta_{i,j}$, respectively. If several vertices have the same probability, the ant will select one of them by random.

In addition, the solution construction of each ant must satisfy the constraints in equation (3). The first constraint, $0 \le n_s \le K$, is automatically satisfied, because $0 \le |\mathrm{V}_s| \le K$; the second constraint, $c_s \in \{c_p, c_f, c_v\}$, is used to compute the cost of each solution; the third constraint, $0 \le H_t \le \phi$, is satisfied if the next vertex is not $v_0^{(s+1)}$ if ant A is at vertex $v_i^{(s)}$, and $\hat{H}_{s+1} > \phi$ or $\hat{H}_{s+2} > \phi$.

Step 3: Pheromone update. After all ants have constructed their solutions, the pheromone trails are updated by the following rule:

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \Delta\tau_{i,j}^{best} \tag{12}$$

where $0 < \rho \leq 1$ is the pheromone evaporation rate; $\Delta\tau_{i,j}^{best}$ is the amount of pheromone released by the ants on $\langle v_i^{(s)}, v_j^{(s+1)} \rangle$, which can be defined as

$$\Delta\tau_{i,j}^{best} = \begin{cases} \frac{1}{C_{best}} & \text{if } \langle v_i^{(s)}, v_j^{(s+1)} \rangle \text{ is in the best solution} \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

Based on the above description, the ACO-based pump scheduling algorithm was summed up as follows:

Algorithm 1. CEPS algorithm

1.	Function CEPS (G)// G is the graph as Figure 2
2.	Set parameters and initialize pheromone trails;
3.	for Itr ← 1 to ItrMax
4.	for i ← 1 to M
5.	$\mathrm{List}_0^i \leftarrow v_s^{(0)}$
6.	for j ← 1 to N + 1
7.	$u \leftarrow \mathrm{List}_{j-1}^i$
8.	$v \leftarrow \operatorname{argmax}\left\{\rho_{u,v}^i \,\middle\vert\, \begin{matrix} \rho_{u,v}^i \text{ computed by (11) and} \\ v \text{ satisfying constraints of (3)} \end{matrix}\right\}$
9.	$\mathrm{List}_j^i \leftarrow v$
10.	end for
11.	end for
12.	$\mathrm{List}_{best}^{Itr}$ ← shortest path of this iteration
13.	C_{best}^{Itr} ← cost of $\mathrm{List}_{best}^{Itr}$
14.	$\mathrm{List}_{best}^{global}$ ← shortest path so far
15.	C_{best}^{global} ← cost of $\mathrm{List}_{best}^{global}$
16.	update τ according to (12) and (13)
17.	end for
18.	return $\mathrm{List}_{best}^{global}$ and C_{best}^{global}
19.	end function

In Algorithm 1, lines 3~17 are the main iterations of the ACO, and $ItrMax$ is the maximum number of iterations. In each iteration, each ant attempts to find a path representing a feasible plan, and ant i stores the solution in $List^i$. At first, all ants are placed at $v_s^{(0)}$ (line 5). Then, all ants construct their solutions by equation (11) and verify the solution feasibility by equation (3) (lines 6-10). Thirdly, lines 12-15 compute the best solution of the current iteration and best-known global solution. Line 16 updates τ to guide the ants to search for the solution in next iteration. Finally, line 18 returns the best solution covering the cost and scheduling plan.

5. EXPERIMENTS AND ANALYSIS

From September 1st to 30th, 2018, several experiments were carried out on the real data of Jinchiling Gold mine in Zhaoyuan, eastern China's Shandong Province, to verify the feasibility of the proposed algorithm. One MDS with $K = 5$ pumps was selected for the experiments from the mine. The power of each pump is $p = 110$kW. The water level threshold of the sump is $\phi = 2.2$ m. The TOU electricity tariff is given in Table 2, where c_p, c_f and c_v are respectively RMB 1.252-yuan, 0.782 yuan and 0.370 yuan. Each day (24h) was divided evenly into $N = 72$ periods with the length $L = 20$ minutes. The smoothing factor was set to $\omega = 0.7$. The symbols and their definitions were given in Table 3 below.

Table 2. TOU electricity tariff

Time period	0:00-6:00	6:00-8:00	8:00-11:00	11:00-18:00	18:00-21:00	21:00-24:00
Tariff (Unit: Yuan)	0.370	0.782	1.252	0.782	1.252	0.370

Table 3. Symbols and definitions

Period	1	2	3	4	5	6	7	8	9
F_s	2.095	2.107	2.118	2.126	2.135	2.147	2.158	2.169	2.180
$\hat{F}_{s+1}$		2.095	2.112	2.126	2.135	2.144	2.158	2.169	2.180
$\hat{F}_{s+2}$			2.095	2.118	2.135	2.143	2.153	2.168	2.180
$\hat{F}_{s+3}$				2.095	2.124	2.144	2.152	2.162	2.179
Period	10	11	12	13	14	15	16	17	18
F_s	2.188	2.200	2.209	2.220	2.221	2.221	2.302	2.310	2.322
$\hat{F}_{s+1}$	2.190	2.197	2.210	2.220	2.230	2.228	2.225	2.336	2.341
$\hat{F}_{s+2}$	2.191	2.201	2.207	2.221	2.230	2.241	2.234	2.227	2.376
$\hat{F}_{s+3}$	2.191	2.201	2.212	2.216	2.232	2.240	2.251	2.240	2.230
Period	19	20	21	22	23	24	25	26	27
F_s	2.329	2.337	2.348	2.356	2.364	2.373	2.382	2.391	2.403
$\hat{F}_{s+1}$	2.343	2.343	2.347	2.358	2.365	2.373	2.382	2.390	2.400
$\hat{F}_{s+2}$	2.369	2.362	2.355	2.357	2.368	2.374	2.381	2.391	2.399
$\hat{F}_{s+3}$	2.417	2.397	2.381	2.367	2.366	2.378	2.383	2.390	2.400

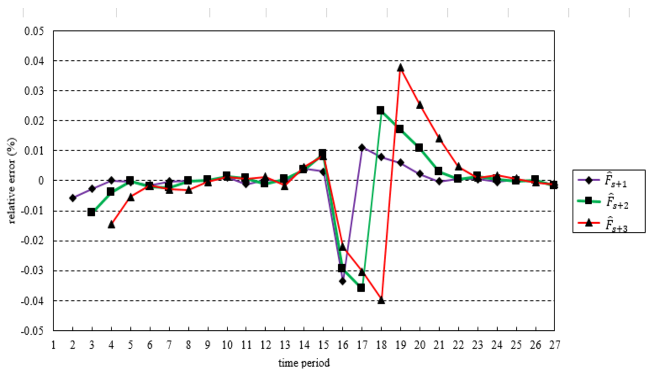

Figure 3. Relative errors of predicted values

Figure 3 records the relative errors of the predicted values of 27 water inflow levels (F_s) in one day. It can be seen that $\hat{F}_{s+1}$ is the most accurate. The mean relative errors of $\hat{F}_{s+1}$, $\hat{F}_{s+2}$ and $\hat{F}_{s+3}$ are, respectively, 0.039 %, 0.066 %, and 0.091 %. The water level variation at 16 causes the greatest prediction error.

Using the above prediction data, the pump scheduling was carried out by Algorithm 1. For convenience, the original pump scheduling plan is denoted as the *original plan*, and the pump scheduling plan after the optimization by Algorithm 1 is denoted as the *optimized plan*. Note that the latter plan is simulated rather than the real scheduling of Jinchiling gold mine.

The ACO parameters were directly extracted from Referen ce [16], which also finds the shortest path in a graph by the A CO, including $M = 30$ ants, $\alpha = 1$, $\beta = 2$, $\rho = 0.9$ and $ItrMax = 300$. The costs of original and optimized plans are compared in Table 4 and Figure 4. The comparison shows th at Algorithm 1 can reduce the mine operation cost by 34.09 % on average from the level of the original plan.

Table 4. Total costs of the original and optimized plans (Unit: RMB yuan)

Day	1	2	3	4	5	6	7	8	9	10
Original	7507	6562	7474	7931	6678	8611	7461	7553	9084	8641
Optimized	4230	3671	4696	5547	5079	4781	5165	5369	6389	6559
Day	11	12	13	14	15	16	17	18	19	20
Original	7932	6254	8785	6823	6307	7835	6502	7533	4655	7198
Optimized	5274	4702	5458	5413	4127	6061	3456	3850	3560	4015
Day	21	22	23	24	25	26	27	28	29	30
Original	7888	8190	6426	6246	7608	7423	6813	7721	6304	7010
Optimized	5151	4661	3480	4019	4562	5666	4274	5362	4504	4981

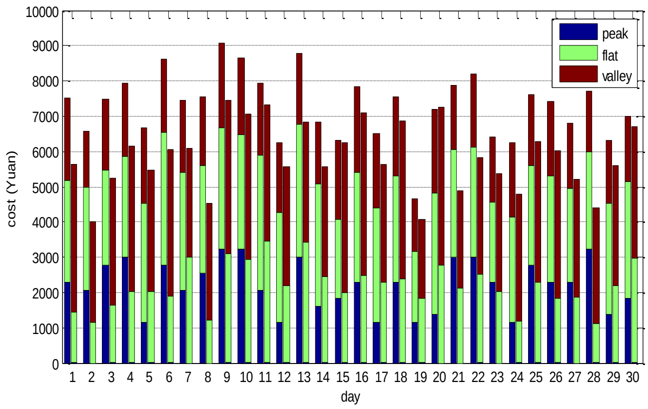

Figure 4. Cost comparison between the original and optimized plans

(In each pair of bars, the left and right bars are respectively the costs of the original and optimized plans.)

Table 5 shows the machine hours of the pumps in peak, flat and valley periods of the two plans. It can be seen that the optimized plan greatly reduces the machine-hours in peak period, and increases the machine-hours in valley period. The results are consistent with Figure 4, where the cost in peak period only accounts for a fraction of the total cost.

Table 5. Machine-hours of the pumps in the original and optimized plans in different periods

Time period	Peak	Flat	Valley
Original	17.67	39.21	54.62
Optimized	2.65	27.99	98.55

6. CONCLUSIONS

With pumps as the main devices, the MDSs often consume lots of electricity in mine production. In most mines, the TOU electricity tariff mechanism is adopted because the pumps only start when the water level in the sump reaches a pre-set threshold. Thus, pump scheduling is a possible way to optimize the MDS energy efficiency. This paper utilizes double exponential smoothing method to predict the water inflow, and employs the ACO to obtain the optimal pump scheduling plan. The proposed pump scheduling method was verified through experiments in a gold mine in China. The experimental results show that the optimized plan can greatly reduce the mine operation cost. The future research will explore the pump scheduling of MDSs with different types of pumps.

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