ENERGY-SAVING SCHEDULING STRATEGY FOR ELEVATOR GROUP CONTROL SYSTEM BASED ON ANT COLONY OPTIMIZATION

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ABSTRACT

Elevator group control scheduling is to dispatch every elevator to serve call requests from different floors based on some certain goal. It's a kind of typical combinatorial optimization problems. Ant colony algorithm is good at solving the discrete combinatorial optimization, its well global optimization ability and quick convergence velocity are both necessary to a scheduling algorithm. Moreover, reducing passengers' waiting and traveling time is the main focus of current dispatching algorithms, neglecting the energy consumed by the elevator system. So it's necessary to research on energy-saving algorithms. For the purpose of elevator group's energy-conservation run, the objective function of energy is built, ant colony model for elevator group control system is created, its optimization mechanism is figured out, and convergence of the algorithm is studied in this paper. Simulation results show the effectiveness of the strategy.

***Index Terms*—** ant colony optimization, elevator group control system (EGCS), dispatching algorithm, energy-saving

1. INTRODUCTION

Elevator Group Control System (EGCS) is an organic whole with three or more elevators installed in buildings, using a control system to schedule the operation of every lift to improve the efficiency of elevator group. Its core is the dispatching algorithms[1]. However, most of current algorithms focus on reducing passengers' waiting and traveling time, neglecting the energy consumed of the elevator system, such as static/dynamic zoning, minimizing waiting time, destination floor registration[2] and so on. For elevator energy-saving, many current studies are about single-car's innovation to prevent from wasting unnecessary energy, for example, gearless tractor[3] and energy feedback technology[4], etc. Not much attention have been paid to group control to reduce energy. In fact, in elevator group control systems, non-reasonable dispatching to the passengers' call will greatly reduce the quality of the effort tried in single-car's energy-saving, even make it become useless, so it's necessary to research on the energy-saving oriented elevator group control dispatching strategy.

The scheduling of elevator group control is to dispatch every elevator to serve different floors' call requests based on some certain objective. It's a kind of typical combinatorial optimization problems. Fast speed dispatching is a high requirement of EGCS, that's to say, choosing the most reasonable plan quickly from many scheduling plans, according to every elevator's current running state and real-time call requests. To satisfy the above requirement, introduce a bionic optimization algorithm, ant colony algorithm, it's good at solving the discrete combinatorial optimization[5,6], its well global optimization ability and quick convergence velocity are both needed by a dispatching algorithm. In addition, the ant algorithm has solved many scheduling and planning problems, such as, TSP[7,8], shop scheduling[9], wireless sensor networks and network routing[10,11], etc.

In view of the two points mentioned, an energy-saving scheduling strategy for EGCS based on ant colony optimization is proposed. Specifically, an energy-cost object function is built, which is the optimization goal, an ant colony group control model based on graph search mechanism is established. In this model, every ant stands for a elevator car, every ant group stands for a elevator group, and various nodes in the graph represent passengers' call requests from different floors, so each realization, every node is traversed by one ant group's elevators, is a scheduling plan. Besides, converting the problem of searching dispatching strategy with least energy-cost to the problem of dynamic TSP, looking for a shortest path, by transforming the value of dispatching energy consumed to the distance among nodes. Furthermore, model constraints decided by the running logic of elevators, optimization mechanism based on pheromone and car-choosing probability, the convergence of the algorithm are also studied in this paper. Simulation results show the validity of this dispatching strategy.

2. ENERGY OBJECTIVE FUNCTION

The goal of energy-saving oriented dispatching strategy in this paper is minimizing the energy-cost. First, the method of calculating energy consumed in EGCS is showed, it's the optimization object function of the ant colony group control model in the following.

The energy cost in EGCS is composed of two parts: one is starting and stopping energy, the other is running energy with uniform speed[12].

$$E = E_a + E_v \tag{1}$$

E stands for the total energy, E_a is the energy of acceleration and deceleration, E_v is uniform running energy . So

$$E = \sum_{r=1}^{n} [E_a(r) + E_v(r)] \tag{2}$$

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n is the number of elevators in group, $E_a(r)$, $E_v(r)$ are the start-stop and running energy of the r^th^ elevator separately. $E_a(r)$ and $E_v(r)$ are computed by equation (3) and (4).

$$E_a(r) = \sum_{s=1}^{q(r)} (p_{(r,s)} \times E_c) \tag{3}$$

$p_{(r,s)}$ is the number of starting-stopping needed by the r^{th} elevator to response to the s^{th} call, $q(r)$ is the total call number answered by the r^{th} elevator. It's assumed that the energy consumption of each starting and stopping is a constant E_c.

$$E_v(r) = \sum_{s=1}^{q(r)} \sum_{t=1}^{p_{(r,s)}} [| n_l(r,s,t) \times \overline{m} + m_{car} - m_{cwt} | g \times h(r,s,t)] \tag{4}$$

$n_l(r,s,t)$ is the total passenger number in the r^{th} elevator's car when it's serving the s^{th} call request at the t^{th} startup, $\overline{m}$ is the average quality of passengers, $h(r,s,t)$ is the floor's displacement between the t^{th} startup and its stop.

In all, the overall energy consumed in EGCS, that is, the energy-cost object function in the following ant colony group control model, could be counted by equation (5).

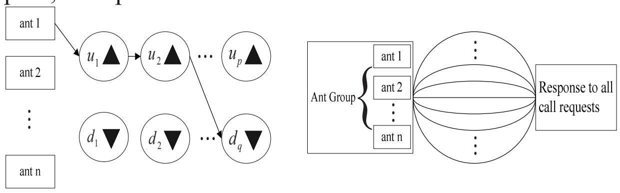
$$\begin{aligned} E = \sum_{r=1}^{n} \{ \sum_{s=1}^{q(r)} (p_{(r,s)} \times E_c) + \\ \sum_{s=1}^{q(r)} \sum_{t=1}^{p_{(r,s)}} [| n_l(r,s,t) \times \overline{m} + m_{car} - m_{cwt} | g \times h(r,s,t)] \} \end{aligned} \tag{5}$$

3. ANT COLONY GROUP CONTROL DISPATCHING STRATEGY

Ant colony algorithm has solved many shortest path optimization problems among multi-nodes (TSP), ant colony group control strategy proposed in this paper is rather similar to it. However, with the combination of elevator group control, the meanings of nodes and path have both been extended, and some specific constraints have been added.

3.1 Ant colony group control model

Assume that, n elevators serve the m floors building, according to the principle of dispatching elevators for call floors, ant colony group control model is shown in Fig.1. In Fig.1 (a), ant1~antn stand for the n elevator cars, nodes $u_1 \sim u_p$ represent different floors with upstairs call requests, while nodes $d_1 \sim d_q$ represent floors with downstairs call. One dispatching plan is a topology which begins with ant group elevators, and traverses all call nodes using ants, that is, every call is served by some certain elevator from the group, for example, ant1→ u_1 → u_2 → d_q in figure1.(a) means No.1 elevator will take and send the up call u_1, u_2 and down call d_q in order. Every dispatching plan is a feasible scheduling path in Fig.1 (b), the optimization is to find the shortest path in the whole. Compared with TSP solved by ant colony algorithm, the meaning of each path's distance has changed in this model, it is defined by the energy consumed of each dispatching plan. So the shortest path stands for the least energy-cost scheduling plan, the optimal solution.



(a) **(b)**

Fig.1. Ant colony group control model

3.2 Model constraints

It is necessary to discuss the model constraints decided by elevators' current running states and running logic when applying the ant colony algorithm to solve the elevator group control problem:

(a). When some elevator plans to serve several up call floor's passengers, the elevator should take the lower floor's passengers first, then the higher floors.

(b). When some elevator plans to serve several down call floor's passengers, the elevator should take the higher floor's passengers first, then the lower floors.

To meet the above restrictions, this paper uses the following method:

Divide all call floors into two parts, up call and down call, then set nodes according to "up call ascending, down call descending", after traffic flow's call signal acquisition is done every periodic interval. Corresponding to Fig.1 (a), there is $u_1 < u_2 < \cdots < u_p$, $d_1 < d_2 < \cdots < d_q$. In the process of ant optimization, ant group elevators will traverse call floors with the sequence $u_1, u_2, \cdots, u_p, d_q, \cdots, d_2, d_1$.

Moreover, without using the tabu list, the method avoids the situation that more than one car is dispatched to one call floor, simplifies the algorithm.

3.3 Group control dispatching Optimization

Dispatching optimization mechanism is shown in this part, which is based on pheromone updating and car-choosing probability.

3.3.1 Pheromone update

τ_{ij} represents the pheromone, i is the serial number of every elevator, j is the number of every call node, path ij means that the i^{th} elevator will serve the j^{th} node. At the initial time, every pheromone has the same set value, constant A, which is also the minimum value. The purpose of setting it is to avoid missing the optimal solution in iterations. When some certain ant group elevators (ant1~antn) succeed in finding a feasible dispatching solution, each passed path's pheromone will be update using the following equation (6):

$$\tau_{ij}(t+1) = \rho \tau_{ij}(t) + \Delta \tau_{ij}^{k} \tag{6}$$

ρ is a weight coefficient, takes value 0~1, $\Delta \tau_{ij}^{k}$ is the path-ij's pheromone incremental changes, it happens after the k^{th} ant group finished a feasible scheduling plan and passed the path ij in it. According to the ant-circle model[13], using formula (7) to calculate $\Delta\tau_{ij}^k$.

$$\Delta\tau_{ij}^k = \begin{cases} C/\Gamma^k & \textit{if group antn passed path ij} \\ 0 & \textit{otherwise} \end{cases} \quad (7)$$

C is a constant, Γ^k is the total energy-cost of the kth ant group's dispatching plan (Global costs).

3.3.2 Car-choosing probability

p_{ij}^k is the probability of the ith elevator from the kth group to serve the jth call floor.

$$p_{ij}^k = \frac{(\tau_{ij})^\alpha \times (1/\Gamma_{ij}^k)^\beta}{\sum_{j\in allowed_k} (\tau_{ij})^\alpha \times (1/\Gamma_{ij}^k)^\beta} \quad (8)$$

$allowed_k$ is the optional call set of the kth group elevators, Γ_{ij}^k is the cost of the ith elevator to take and send the passengers from the jth call floor (Local costs), α, β are both coefficients.

3.3.3 Optimization mechanism

Ant colony group control strategy searches the optimal solution by iterations of group elevators. For every group, the choice, every call floor is served by which elevator, is decided by p_{ij}^k which is determined by τ_{ij} and $1/\Gamma_{ij}^k$. τ_{ij} updates its value continuously, the pheromone of the path which is from the feasible dispatching plan with lower energy consumed will be bigger, C/Γ^k in equation (7) is a consideration about the global energy-cost of one scheduling plan. While $1/\Gamma_{ij}^k$ is to make sure that dispatching elevators for every call floor is low local costs. After iterations, according to the positive feedback mechanism of ant colony algorithm, this paper's strategy could find the optimal dispatching plan with least energy-cost.

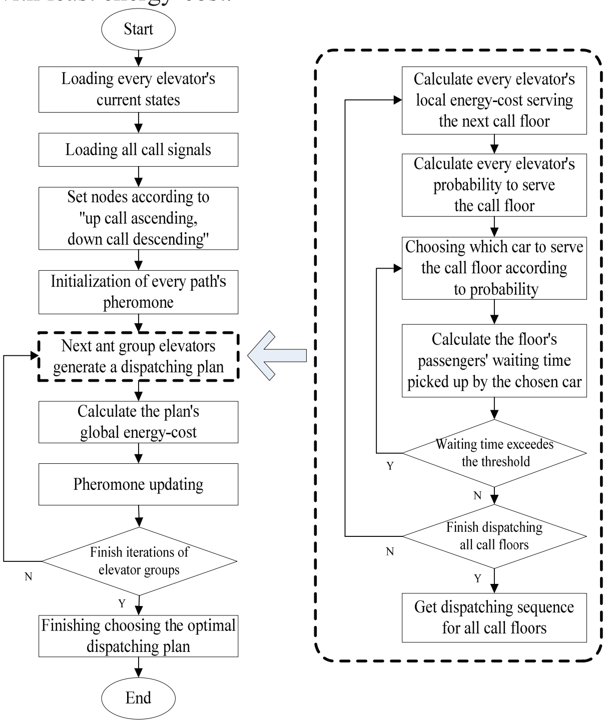


Fig.2. Flow chart of ant colony group control strategy

Fig.2 is the flow chart of energy-saving oriented ant colony group control strategy. In the left figure, first, the strategy loads every elevator's current states and all call signals, sets nodes, initializes every pheromone, then, starts iterations. In every iteration, every ant group elevators generates a dispatching plan, calculates the global cost Γ^k by formula (5), updates pheromones. To be specific, each dispatching plan's generation needs the steps shown in the right figure.

4. ALGORITHM'S CONVERGENCE

The convergence proof of ant colony group control algorithm is as follows[14]:

Lemma Every Pheromone τ_{ij} has an upper bound $\tau_{\max} = C/(\Gamma_{\min}\cdot\rho)$.

Proof Assume the initial pheromone of every path is τ_0, after an iteration, its max increment is $C/\Gamma_{\min}$, so the max pheromone is $(1-\rho)\tau_0 + C/\Gamma_{\min}$, after two iterations, it's $(1-\rho)^2\tau_0 + (1-\rho)C/\Gamma_{\min} + C/\Gamma_{\min}$, and so on. Hence, due to evaporation of it, after θ iterations, the pheromone should be smaller or equal to:

$$\tau_{\max} = (1-\rho)^\theta \tau_0 + \sum_{i=1}^{\theta}(1-\rho)^{\theta-i} C/\Gamma_{\min} \quad (9)$$

Because $0 < \rho \le 1$, $\tau_{\max}$ converges to $C/(\Gamma_{\min}\cdot\rho)$.

Theorem Let $P^*(\theta)$ be the probability that the algorithm finds an optimal solution at least once with the first θ iterations. Then, for a sufficiently large θ, it holds that $\lim_{\theta\to\infty} P^*(\theta) = 1$.

Proof Due to the pheromone limits $\tau_{\min}$ and $\tau_{\max}$, let $\eta = 1/\Gamma_{ij}^k$, so η also has an upper and a lower bound. A trivial lower bound for car-choosing probability can be:

$$\hat{p}_{\min} = \frac{\tau_{\min}^\alpha \eta_{\min}^\beta}{(D-1)\tau_{\max}^\alpha \eta_{\max}^\beta + \tau_{\min}^\alpha \eta_{\min}^\beta} \quad (10)$$

D is optional total call floor numbers at a moment, so, arbitrary dispatching solution, including any optimal one, can be generated with a probability $\hat{p} \ge \hat{p}_{\min}^n > 0$, where n is the number of total calls. Because it's enough that one ant finds an optimal solution, a lower bound for $P^*(\theta)$ is given by $\hat{P}^*(\theta) = 1-(1-\hat{p})^\theta$. By choosing a sufficiently large θ, this probability can be larger than any value $1-\varepsilon$ ($\varepsilon > 0$, is an arbitrary small), so we have $\lim_{\theta\to\infty} P^*(\theta) = 1$.

The above result shows that, the strategy in this paper could converge to the optimal dispatching solution with least energy-cost.

5. SIMULATION

To illustrate the effectiveness of the proposed scheduling strategy, the simulation is finished by virtual elevator environment of our lab[15]. Different algorithms' performance can be tested in the software by importing algorithms' dll (dynamic link library) program. Table I shows the specifications of the EGCS.

TABLE I
SPECIFICATIONS OF EGCS

Items	value
Number of Floors	16
Number of Elevators	4
Floor Distance[m]	3
Velocity[m/s]	2.5
Acceleration[m/s/s]	1
Jerk[m/s/s/s]	1.8
Car Capacity[person]	12
Time of Opening & Closing door[s]	4
Time of Passenger's Loading & unloading[s/person]	1

Initial parameters in the energy object function (offered by OTIS elevator company) : starting-stopping energy 22.5 kJ, car quality 800 kg, counter weight quality 900 kg, passengers' average quality 65 kg.

Simulations have two parts: (a) For different traffic flows, comparing the performance of this paper's strategy with other dispatching algorithms; (b) For some certain flow, research on the convergence of the strategy.

(a) Traffic flows: 3 kinds of 60 min traffic flows, uppeak, random interfloor and downpeak. Scheduling strategy: static, min waiting time and the method proposed in this paper. Parameters of the ant colony: $\alpha = 1$, $\beta = 5$, $\rho = 0.99$ [16], iterations 200, long waiting time threshold 60 sec. Simulation results are listed below.

TABLE II
RESULTS OF SIMULATION

Traffic Flow	Dispatching Strategy	Average Waiting Time(s)	Energy-cost of EGCS(kJ)
Uppeak	Static	32.50	36380.66
	Min Waiting Time	39.47	38202.14
	Ant Colony	**49.80**	**33314.89**
Random Interfloor	Static	63.25	21624.82
	Min Waiting Time	36.29	22135.11
	Ant Colony	**37.13**	**21338.74**
Downpeak	Static	42.15	39729.03
	Min Waiting Time	35.55	40526.38
	Ant Colony	**32.31**	**36364.63**

Results show that, contrast with the other 2 algorithms, the ant colony group control algorithm could reduce the system's energy consumed effectively in 3 traffic flows, especially in peak patterns, uppeak and downpeak, because of the numerous and crowed flows. While for random interfloor pattern, the energy-conservation effect of the strategy is not obvious. In addition, some waiting time has been sacrificed to pursue the lower energy-cost by this strategy, for example, the waiting time in the uppeak is a little longer, though within the acceptable range. This is the reason to set the threshold, energy-cost should be saved as much as possible without too more loss of time performance.

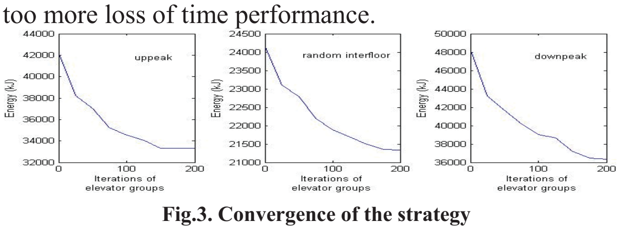


Fig.3. Convergence of the strategy

(b) Fig.3 shows the convergence of the strategy. The optimization could converge to the least-energy solution within 200 iterations for all these 3 traffic flows.

6. CONCLUSIONS

Ant colony algorithm and elevator group control are combined in this paper. To solve the problem of elevators' energy-saving running, energy object function is built, energy-conservation oriented ant colony group control strategy is proposed. Specifically, the following aspects are studied, the ant colony elevator model, model's constraints, optimization mechanism based on pheromone and car-choosing probability, as well as convergence. Simulation results show that the proposed strategy can reduce the EGCS's energy effectively.

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