Elevator Group Scheduling for Peak Flows Based on Adjustable Robust Optimization Model

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***Abstract*— Group elevator scheduling has received more attention with the increase demand of high-rise buildings. The key factor which affects the transportation performance's further improvement is the uncertainty of traffic flow. Moreover, peak flows are rather common in buildings, while their uncertainties aren't considered by most algorithms, that could result in larger scheduling price. It's feasible to solve the problem of uncertain peak flows' dispatching with the method of Adjustable Robust Optimization (ARO). In this paper, ARO theory is put into practice, an ARO model for peak flows of Elevator Group Control System (EGCS) is built, the idea of modeling is shown, and an ARO dispatching approach is proposed. Simulation results demonstrate the validity of the approach. Finally, future trends of ARO group scheduling are summarized.**

Key words: Elevator Group Scheduling, Peak Flows, Adjustable Robust Optimization (ARO)

I. INTRODUCTION

THE function of EGCS is to schedule three or more elevators set in a building with the goal of reducing the total dispatching price, so as to improve lifts' efficiency and offer better service to passengers [1]. Scheduling cores are dispatching algorithms of different elevator traffic flows which are time series, reflecting time-variant calling passenger numbers of different floors. At present, there are several common scheduling approaches applied in EGCS, such as, conventional minimizing waiting time, novel scheduling based on exact calculation of expected waiting times [2], fuzzy group control [3] and so on. However, the uncertainty of elevator traffic flow isn't considered by all above methods, while it's the key source of affecting the EGCS's performance. Moreover, the peak flow is a kind of common elevator flows, [4-6] study control methods of it. It could be a feasible way to further improve group control performance by dealing with the peak flow's uncertainties.

To solve the uncertain peak flow's scheduling, we introduce the method of Adjustable Robust Optimization (ARO). As the basis of ARO, Robust optimization (RO) is a new method to solve the uncertain optimization problems [7-9]. It uses the "set" to depict uncertainty of the data. The solution of the robust counterpart will satisfy all demands in a given bounded uncertain set. While ARO is an extension of RO proposed by Ben-Tal [10-11]. Ben-Tal divides decision variables into two parts: non-adjustable variables and adjustable variables. The former ones are isolated from other information, while the latter ones can be made based on some other variables, in a sense, they are adaptive. So far, there are many applications based on RO theory in different fields, for instance, uncertain supply chain optimization [12], crude oil scheduling [13] and multi-site production planning [14], etc. Nevertheless, examples of putting ARO into practice are rather seldom. So it's an innovative work to apply the ARO theory to elevator group control.

The contribution of this paper is using ARO method to solve the scheduling optimization of elevator uncertain peak flows. Specifically, basic theory of ARO is given first, group dispatching principle, peak flow's scheduling problem are introduced, an EGCS's ARO model is built, its Adjustable Robust Counterpart (ARC) is researched, and an ARO scheduling approach for EGCS is proposed. Simulation results show the effectiveness of this approach.

II. BASIC THEORY

A. RO—ARO's Basis

An Uncertain Linear Optimization problem is a collection

$$\left\{\min_x c^T x : Ax \le b\right\}_{(c,A,b)\in Z} \tag{1}$$

Here $x \in R^n$ is the vector of decision variables, $c \in R^n$ and $A \in R^{m\times n}$ are objective and constraint matrix respectively, $b \in R^m$ is the right hand side vector, while Z is the uncertain set.

A vector x is a robust feasible solution, if it satisfies all realizations of the constraints from the uncertain set, that is

$$Ax \le b \quad \forall (c,A,b)\in Z \tag{2}$$

Given a candidate solution x , the robust value $\hat{c}(x)$ of the objection in LO_U at x is the largest value of $c^T x$ over all realizations of the data from the uncertain set:

$$\hat{c}(x) = \sup_{(c,A,b)\in Z} c^T x \tag{3}$$

The Robust Counterpart (RC) transformation is to make uncertain optimizations become certain ones. The RC of the uncertain LO problem is the optimization problem of

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minimizing the robust value of the objective over all robust feasible solutions [15].

$$\min_x \left\{ \hat{c}(x) = \sup_{(c,A,b)\in Z} c^T x:\ Ax \le b \quad \forall (c,A,b) \in Z \right\} \tag{4}$$

B. ARO Theory

ARC considers linear programs with uncertain parameters, lying in some prescribed uncertain set, where part of the variables must be determined before the realization of the uncertain parameters (non-adjustable variables), while the other part are variables that can be chosen after the realization (adjustable variables).

According to the above formula (1), let $x = \left[u^T \ v^T\right]^T$, $A = \left[U \ V\right]$, where u is non-adjustable, v is adjustable. And it's assumed that c is a certain matrix, because if not, it's easy to put it to the constraint functions by adding slack variables. So we have

$$\left\{ \min_{u,v} c^T \begin{pmatrix} u \\ v \end{pmatrix} : Uu + Vv \le b \right\}_{(U,V,b)\in Z} \tag{5}$$

We assume, without loss of generality, the uncertain linear programming problem (5) is normalized and thus rewrite this problem as a family

$$\left\{ \min_{u,v} c^T u : Uu + Vv \le b \right\}_{(U,V,b)\in Z} \tag{6}$$

And its RC is given by:

$$\left\{ \begin{array}{l} \min_u c^T u \\ \exists v \ \forall (U,V,b) \in Z : Uu + Vv \le b \end{array} \right\} \tag{7}$$

Its Adjustable Robust Counterpart (ARC) is given by:

$$\left\{ \begin{array}{l} \min_u c^T u \\ \forall (U,V,b) \in Z \ \exists v : Uu + Vv \le b \end{array} \right\} \tag{8}$$

In most cases the ARC is computationally intractable (NP-hard). This difficulty is addressed by restricting the adjustable variables to be affine functions of the uncertain data [10]. The ensuing Affinely Adjustable Robust Counterpart (AARC) problem, in certain important cases, is equivalent to a tractable optimization problem, and in other cases, has a tight approximation which is tractable. In the formula (8), if v is an affine function of ξ, $v = (w + W\xi)$, the AARC of (8) is given by

$$\left\{ \begin{array}{l} \min_{u,w,W} c^T u \\ \forall (U,V,b) \in Z : Uu + V\left(w + W\xi\right) \le b \end{array} \right\} \tag{9}$$

III. PROBLEM FORMULATION

Scheduling strategy of EGCS is to decide which car in group to serve every floors' calling passengers to achieve some goals based on traffic flows and each elevator's running state.

Consider the situation, n elevators serve a building with m floors, scheduling solutions could be expressed as an up calling dispatching plan matrix X_U and a down calling one X_D, with m-1 rows and n columns respectively. The reason why the row number of them is m-1, not m, is that, there aren't up calling requests on the top floor, and similarly, there aren't down calling requests on the bottom floor. In X_U / X_D, the element of α_{th}-row and β_{th}-column means to dispatch the No. β elevator to pick up the $\alpha_{th} / (\alpha+1)_{th}$ floor's up/down calling passengers or not by the symbol one or zero.

To be specific, there's an example, 4 elevators (car capacity: 12 people) serve a 16-floor building for illustration.

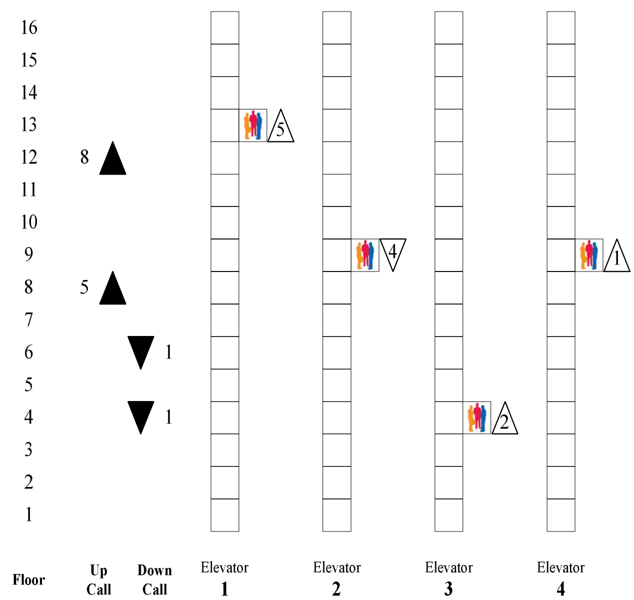

Fig. 1. Example of group scheduling.

In Fig.1, black solid arrows stand for all calling requests' numbers and directions at some time, there are one and one down calling passengers on the 4th and 6th floor, and five and eight up calling people on the 8th and 12th floor. While white hollow arrows represent elevators' running directions and people numbers inside every car at the time, according to Fig.1, No.1, 3 and 4 elevators are upward cars, in which there are five, two and one passengers separately, while No.2 is downward with four people.

$$X_U = \begin{array}{c} 15 \\ \vdots \\ 12 \\ \vdots \\ 8 \\ \vdots \\ 1 \end{array} \begin{bmatrix} 0 & 0 & 0 & 0 \\ & & \vdots & \\ 0 & 0 & 0 & 1 \\ & & \vdots & \\ 0 & 0 & 1 & 0 \\ & & \vdots & \\ 0 & 0 & 0 & 0 \end{bmatrix}_{15\times 4}, \quad X_D = \begin{array}{c} 16 \\ \vdots \\ 6 \\ \vdots \\ 4 \\ \vdots \\ 2 \end{array} \begin{bmatrix} 0 & 0 & 0 & 0 \\ & & \vdots & \\ 0 & 1 & 0 & 0 \\ & & \vdots & \\ 0 & 1 & 0 & 0 \\ & & \vdots & \\ 0 & 0 & 0 & 0 \end{bmatrix}_{15\times 4} \tag{10}$$

For the above example, the two matrices in (10) compose a scheduling solution at that time. According to it, the system will dispatch No. 3 and 4 elevator to take the 8th and 12th floors' up calling people separately, and No. 2 elevator to serve the 4th and 6th floors' down callings successively.

As for peak traffic flows, they are rather common in buildings, including not only up-peak and down-peak flows, but also meeting flows and some others, when many people need to reach the same destination from different floors and leave there at the same time almost. However, general scheduling algorithms have a natural shortcoming, that is, EGCS will send one elevator and only one to serve a calling floor in the first step, without considerations of the uncertain calling passenger number. If the number surpasses the max capacity of the car, the remaining passengers will have to push the outside calling button again and wait for another elevator's coming next time, EGCS will pick up them in the second step. And if there are still some people left, more steps will be done.

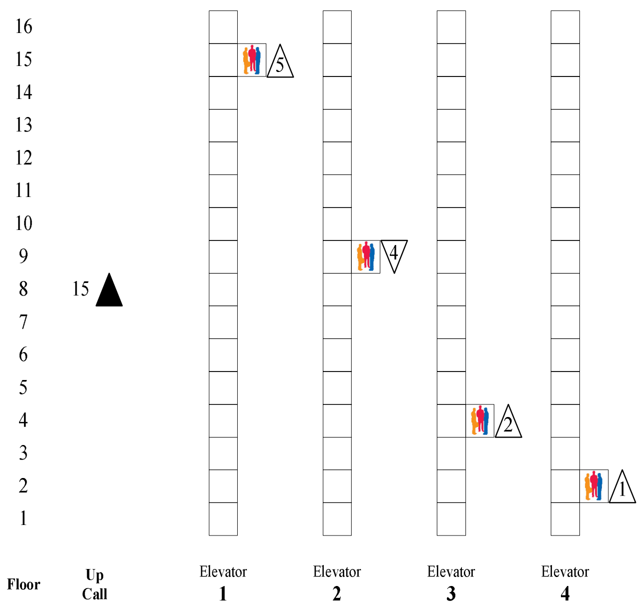

Fig. 2. Example of peak scheduling.

Fig. 2 is an example of the above situation. When there are 15 up calling passengers on the 8th floor, according to every elevator's running state, it's not reasonable to dispatch the 3rd or 4th car solely to pick them, because it will increase some people's waiting time and total scheduling price severely. Actually, an optimal solution is to dispatch the 3rd and 4th cars together to serve, and this is the basic idea of ARO modeling proposed in this paper. And our ARO approach is to find the most reasonable dispatching solution for peak flows with least cost.

IV. ARO SCHEDULING APPROACH

There are three regular steps to apply the ARO theory into practice, first, ARO modeling, second, ARC transformation, converting an uncertain optimization (ARO) into certain ones (ARC) , and finally, solving of certain optimization.

In this section, the multi-objective price of EGCS is shown, the uncertain set of traffic flow is defined, and based on them, an ARO model for peak flow is built, an ARO scheduling approach is proposed.

The optimal objective of the ARO model is to reduce the total scheduling price. In general, the objective contains many aspects, such as passengers' waiting time, traveling time, crowding and so on. Formula (11) is used to calculate the price.

$$F(\rho,\theta)=\omega_1\frac{f_w(\rho,\theta)}{f_w^*}+\omega_2\frac{f_t(\rho,\theta)}{f_t^*}+\omega_3\frac{f_c(\rho,\theta)}{f_c^*} \quad (11)$$

$f_w(\rho,\theta)$: waiting time cost of the ρ_{th} elevator to serve calling passengers on the θ_{th} floor

f_w^* : waiting time expectation

$f_w(\rho,\theta)$: traveling time cost of the ρ_{th} elevator to serve calling passengers on the θ_{th} floor

f_w^* : traveling time expectation

$f_w(\rho,\theta)$: crowding cost of the ρ_{th} elevator to serve calling passengers on the θ_{th} floor

f_w^* : crowding expectation

The performances among waiting, traveling time and crowding are always contradictory. For instance, it will longer the traveling time of the people inside the car to stop and pick up other waiting passengers. Besides, low crowding means a more comfortable environment, however, it's no doubt that the transportation efficiency of EGCS will be reduced. So we need to tune the weights, ω_1 , ω_2 and ω_3 , according to different traffic flows [16]. For peak flows, it's reasonable to consider the waiting and traveling time first to ensure people could arrive at the destination quickly. As for some other flows, we may pay more attention to people's feelings by increase the weight value ω_3 .

Moreover, because ARO is used to solve bounded uncertain optimization problems, in the approach studied in this paper, the uncertainty of traffic flow is expressed as follows:

$$p_{Ui}\in[\hat{p}_{Ui}-\overline{p}_{Ui},\hat{p}_{Ui}+\overline{p}_{Ui}] \quad (12)$$

$$p_{Dj}\in[\hat{p}_{Dj}-\overline{p}_{Dj},\hat{p}_{Dj}+\overline{p}_{Dj}] \quad (13)$$

p_{Ui} : up call passenger actual value of i_{th} floor

$\hat{p}_{Ui}$: up call passenger predictive value of i_{th} floor

$\overline{p}_{Ui}$: up call passenger disturbance limit of i_{th} floor

p_{Dj} : down call passenger actual value of j_{th} floor

$\hat{p}_{Dj}$: down call passenger predictive value of j_{th} floor

$\overline{p}_{Dj}$: down call passenger disturbance limit of j_{th} floor

Based on the multi-objective price and the bounded uncertain set, the ARO model for peak flows of EGCS is given by:

$$\min \quad F$$

$$
\text{s.t.}\quad
\begin{cases}
\Phi_{Ui} = \left\lfloor \dfrac{p_{Ui}}{C} \right\rfloor & (14)\\
\Phi_{Dj} = \left\lfloor \dfrac{p_{Dj}}{C} \right\rfloor & (15)\\
x_{Ui} = x_{Ui,0} + \sum_{k=1}^{\Phi_{Ui}} x_{Ui,k} \quad i \in \{up\ call\ floors\ set\} & (16)\\
x_{Dj} = x_{Dj,0} + \sum_{l=1}^{\Phi_{Dj}} x_{Dj,l} \quad j \in \{down\ call\ floors\ set\} & (17)\\
F = \sum_{i=1}^{m-1} F_{Ui} + \sum_{i=2}^{m} F_{Dj} & (18)\\
\Omega = [\omega_1 \quad \omega_2 \quad \omega_3] & (19)\\
F_{Ui} = \begin{bmatrix} Q_{Ui,0} & Q_{Ui,1} & \cdots & Q_{Ui,\Phi_{Ui}} \end{bmatrix} \begin{bmatrix} \Omega\Theta_{Ui} x_{Ui,0} \\ \Omega\Theta_{Ui} x_{Ui,1} \\ \vdots \\ \Omega\Theta_{Ui} x_{Ui,\Phi_{Ui}} \end{bmatrix} & (20)\\
Q_{Ui,0} = Q_{Ui,1} = \cdots = Q_{Ui,\Phi_{Ui}-1} = C & (21)\\
Q_{Ui,\Phi_{Ui}} = p_{Ui} - C\Phi_{Ui} & (22)\\
\Theta_{Ui} = \begin{bmatrix} f_{1(Ui,1)} & f_{1(Ui,2)} & \cdots & f_{1(Ui,n)} \\ f_{2(Ui,1)} & f_{2(Ui,2)} & \cdots & f_{2(Ui,n)} \\ f_{3(Ui,1)} & f_{3(Ui,2)} & \cdots & f_{3(Ui,n)} \end{bmatrix} & (23)\\
F_{Dj} = \begin{bmatrix} Q_{Dj,0} & Q_{Dj,1} & \cdots & Q_{Dj,\Phi_{Dj}} \end{bmatrix} \begin{bmatrix} \Omega\Theta_{Dj} x_{Dj,0} \\ \Omega\Theta_{Dj} x_{Dj,1} \\ \vdots \\ \Omega\Theta_{Dj} x_{Dj,\Phi_{Dj}} \end{bmatrix} & (24)\\
Q_{Dj,0} = Q_{Dj,1} = \cdots = Q_{Dj,\Phi_{Dj}-1} = C & (25)\\
Q_{Dj,\Phi_{Dj}} = p_{Dj} - C\Phi_{Dj} & (26)\\
\Theta_{Dj} = \begin{bmatrix} f_{1(Dj,1)} & f_{1(Dj,2)} & \cdots & f_{1(Dj,n)} \\ f_{2(Dj,1)} & f_{2(Dj,2)} & \cdots & f_{2(Dj,n)} \\ f_{3(Dj,1)} & f_{3(Dj,2)} & \cdots & f_{3(Dj,n)} \end{bmatrix} & (27)\\
x_{(Ui,s)\cdot q} = \{0,1\} \quad s = 0,1,\cdots,\Phi_{Ui} \quad q = 1,2,\cdots,n & (28)\\
x_{(Dj,t)\cdot r} = \{0,1\} \quad t = 0,1,\cdots,\Phi_{Dj} \quad r = 1,2,\cdots,n & (29)\\
[1 \quad 1 \quad \cdots \quad 1]_{1\times n}\, x_{Ui,s} = \{0,1\} & (30)\\
[1 \quad 1 \quad \cdots \quad 1]_{1\times n}\, x_{Dj,t} = \{0,1\} & (31)\\
x_{Ui,s} \neq x_{Ui,s+1} & (32)\\
x_{Dj,t} \neq x_{Dj,t+1} & (33)
\end{cases}
$$

Variable declarations are listed below:

m – building floor number

n – elevator number

F – total dispatching price

$p_{Ui}\,|_{i=1,2,\cdots,m-1}$ – up call passenger number of i_{th} floor (uncertain parameter)

$p_{Dj}\,|_{j=2,3,\cdots,m}$ – down call passenger number of j_{th} floor (uncertain parameter)

C – car capacity

$\lfloor A \rfloor$ – max integer which is less than A

Φ_{Ui} – beyond capacity coefficient of i_{th} floor's up call passengers

Φ_{Dj} – beyond capacity coefficient of j_{th} floor's down call passengers

x_{Ui} – partial dispatching solution for i_{th} floor's up call passengers

$x_{Ui,0}$ – basic solution for i_{th} floor's up call passengers

$x_{Ui,y}\,|_{y=1,\cdots,\Phi_{Ui}}$ – extended solution for i_{th} floor's up call passengers

x_{Dj} – partial dispatching solution for j_{th} floor's down call passengers

$x_{Dj,0}$ – basic solution for j_{th} floor's down call passengers

$x_{Dj,z}\,|_{z=1,\cdots,\Phi_{Dj}}$ – extended solution for j_{th} floor's down call passengers

F_{Ui} – price of EGCS serving i_{th} floor's up call requests

F_{Dj} – price of EGCS serving j_{th} floor's down call requests

Ω – weights matrix of price function

Θ_{Ui} – subfunction matrix of price function corresponding to i_{th} floor's up calls

$Q_{Ui,g}\,|_{g=0,1,\cdots,\Phi_{Ui}}$ – people number which is distributed to some certain elevator, coming from the total i_{th} floor's up call passengers

$f_{1(Ui,u)}$ – unit waiting time cost for u_{th} elevator to respond to i_{th} floor's up calls

$f_{2(Ui,u)}$ – unit traveling time cost for u_{th} elevator to respond to i_{th} floor's up calls

$f_{3(Ui,u)}$ – unit crowding cost for u_{th} elevator to respond to i_{th} floor's up calls

Θ_{Dj} – subfunction matrix of price function corresponding to j_{th} floor's down calls

$Q_{Dj,h}\,|_{h=0,1,\cdots,\Phi_{Dj}}$ – people number which is distributed to some certain elevator, coming from the total j_{th} floor's down call passengers

$f_{1(Dj,v)}$ – unit waiting time cost for v_{th} elevator to respond to j_{th} floor's down calls

$f_{2(Dj,v)}$ – unit traveling time cost for v_{th} elevator to respond to j_{th} floor's down calls

$f_{3(Dj,v)}$ – unit crowding cost for v_{th} elevator to respond to j_{th} floor's down calls

$x_{(Ui,s)\cdot q}$ – q_{th} element of s_{th} dispatching component solution corresponding to i_{th} floor's up calls

$x_{(Dj,t)\cdot r}$ – r_{th} element of t_{th} dispatching component solution corresponding to j_{th} floor's down calls

This ARO model is used to solve the peak flow problem. To be specific, beyond capacity coefficients in formula (14), (15), which depict the relationship between calling passenger numbers and car's max capacity, Φ_{Ui} and Φ_{Dj} are created for offering foundations of adjustable decision solutions' adaptive changes. Every final dispatching plan (total solution), X_U and X_D , are composed of different floors' partial solutions, x_{Ui} and x_{Dj} . Moreover, each partial is acquired based on (16) and (17), where $x_{Ui,0}$ and $x_{Dj,0}$ are non-adjustable decisions (basic solution) , $x_{Ui,k}$ and $x_{Dj,l}$ are adjustable ones (extended solution) . Its idea is that, for calling people on some floor, EGCS will send one car to serve at least according to non-adjustable solutions, while adjustable solutions, if exist, will decide whether to send more elevators to react based on parameters Φ_{Ui} and Φ_{Dj} . The total scheduling price could be calculated as (18), including overall up and down call serving prices. Objective function's weights in (19) should be tuned to adapt to different flows mentioned before. Up call dispatching price's calculating method is shown by (20) ~ (23). The price is the sum of every dispatched car's scheduling cost, which could be counted by that, up call people numbers assigned to each dispatched one multiply respective unit prices, containing waiting time, traveling time and crowding. Similarly, down call prices correspond to (24) ~ (27). In addition, (28) ~ (33) are all constraints of EGCS. (28), (29) guarantee every element of each component solution is zero or one. And (30), (31) mean that, if the element "one" exists in one component solution, only one at most. Lastly, each basic and extended solution of partial ones shouldn't be same, avoiding dispatching one car more than once, which is ensured by formula (32) and (33).

To get least-price scheduling solutions for peak flows, it's necessary to transform the uncertain programming into a certain optimization by ARC. The difference between the ARO and its ARC are 4 formulae's change, that's (14), (15), (22) and (26), they need to be converted to

$$\Phi_{Ui} = \left\lfloor \frac{\hat{p}_{Ui} + \overline{p}_{Ui}}{C} \right\rfloor \tag{14*}$$

$$\Phi_{Dj} = \left\lfloor \frac{\hat{p}_{Dj} + \overline{p}_{Dj}}{C} \right\rfloor \tag{15*}$$

$$Q_{Ui,\Phi_{Ui}} = \hat{p}_{Ui} + \overline{p}_{Ui} - C\Phi_{Ui} \tag{22*}$$

$$Q_{Dj,\Phi_{Dj}} = \hat{p}_{Dj} + \overline{p}_{Dj} - C\Phi_{Dj} \tag{26*}$$

Then we could solve the certain optimization of ARC with the intelligent solving methods, such as particle swarm algorithm and so on. Finally, optimal scheduling solutions with least price are acquired.

V. SIMULATION

Simulation work which verifies the effectiveness of the proposed ARO scheduling strategy is done with the help of virtual elevator environment of our lab [17]. Different algorithms' performance can be tested in the software by importing algorithms' dll (dynamic link library) programs. Besides, LINGO (Linear Interactive and General Optimizer) software is used to solve certain optimization of ARC. Furthermore, an interface between LINGO and VC is also developed to realize the scheduling approach. Table I shows the specifications of the simulation system.

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

Four kinds of peak traffic flows have been chosen to compare ARO method's performances (Average Waiting Time, Traveling Time and Crowding) with other algorithms, including Static Zoning, Min Waiting Time, Multi-Agent.

Specific settings of 4 flows are as follows:

1) Up-peak flow: 500 persons, from the hall floor to upper floors

2) Down-peak flow: 500 persons, from different floors to the hall floor

3) Before-meeting flow: 500 persons, from different floors to the meeting room which is on the 8th floor to attend the conference

4) After-meeting flow: 500 persons, after the meeting, from the 8th floor to different destinations

Simulation results are listed in Table II, III, IV and V.

TABLE II
SIMULATION OF UP-PEAK FLOW

Algorithm	Avg. Waiting Time (s)	Avg. Traveling Time (s)	Avg. Crowding (person)
Static	41.67	34.87	7.82
Min-Waiting	30.16	33.56	5.34
Multi-Agent	28.32	34.13	5.64
ARO	**24.78**	**34.31**	**7.43**

TABLE III
SIMULATION OF DOWN-PEAK FLOW

Algorithm	Avg. Waiting Time (s)	Avg. Traveling Time (s)	Avg. Crowding (person)
Static	36.59	34.82	6.65
Min-Waiting	33.48	31.25	5.28
Multi-Agent	32.91	32.47	5.67
ARO	**29.99**	**32.36**	**6.84**

TABLE IV
SIMULATION OF BEFORE-MEETING FLOW

Algorithm	Avg. Waiting Time (s)	Avg. Traveling Time (s)	Avg. Crowding (person)
Static	27.38	29.40	4.96
Min-Waiting	24.42	28.03	4.77
Multi-Agent	23.11	28.51	4.32
ARO	**21.62**	**28.37**	**5.11**

TABLE V
SIMULATION OF AFTER-MEETING FLOW

Algorithm	Avg. Waiting Time (s)	Avg. Traveling Time (s)	Avg. Crowding (person)
Static	24.39	32.96	5.67
Min-Waiting	21.37	30.72	5.44
Multi-Agent	22.08	29.88	5.59
ARO	**19.04**	**30.98**	**5.62**

From Table II and III, we can see that, for the up-peak and down-peak flows, the average waiting time of ARO is best among four algorithms. While the average traveling time of ARO is not least, because scheduling more than one car to take peak flow of a floor could decrease outside passengers' waiting time actually and increase traveling time of the people inside the dispatched cars as well. In addition, the crowding performance of ARO is a little bigger than some other methods as a result of the ARO strategy's high transportation efficiency, making full use of every car's carrying ability. Besides, the reason why the ARO's waiting time of up-peak is shorter than the one of down-peak for 500 people and the traveling time inversely, is that, in up-peak, time performances are wasted mostly for passengers' traveling, not waiting, while in down-peak, an opposite situation occurs.

Furthermore, the before-meeting flow is similar with the down-peak flow with the characteristic that passengers arrive at a certain floor from various ones. While the after-meeting flow has the same point with the up-peak flow, people leave a certain floor to different ones.

From Table IV and V, performances of ARO scheduling method are rather well, too. The average waiting-traveling time and crowding are both less than the ones of up-down peak for the same number of passengers, because the meeting floor is in the middle of the building and meeting flows are two-way.

VI. CONCLUSION

Within this paper, ARO method is applied to solve uncertainties of peak flows' scheduling optimization. To be specific, an ARO model for EGCS is built, its ARC transformation is studied, and an ARO dispatching approach is proposed. Finally, numerical simulation tests offer a practical foundation of the strategy.

In future work, ARO scheduling method could be perfected by the following way. Energy-cost object could be considered in multi-objective optimization to save the system energy consumption to some extent. If so, the scheduling will be more reasonable. Actually, time and crowding performances aren't sole optimal standards.

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