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A Genetic Algorithm Based Elevator Dispatching Method For Waiting Time Optimization

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Abstract: Elevator group control is one of the important issues in vertical transportation systems in buildings. For an efficient group control algorithm it is required to overcome some optimization problems. From the perspective of quality of service two fundamental parameters needed to be optimized are waiting time and journey time. Elevator group control algorithms can be developed based on soft computing methods used for optimization. In the last decade Genetic Algorithm(GA) has attracted researchers' attention as the suitability for the encoding car dispatching problem. In this study we enhance a previous study suggested for optimization of waiting time. The proposed method reduces average waiting time and uses a simpler encoding approach which results in efficiency in terms of computational cost. We explicitly demonstrate the method on the referred scenario for the purpose of visualization and insight.

Keywords: Genetic algorithm, elevator group control, elevator dispatching method, waiting time optimization

1. INTRODUCTION

Until 2000s classical methods have been adapted as convention for elevator group control systems (EGCS). With the advance in soft computing, alternative researches using intelligent methods for EGCS have emerged. Tyni and Ylinen (2001) proposed using Genetic Algorithm for car routing in single-deck systems for waiting time optimization. With its suitability for the encoding car dispatching problem Genetic Algorithm has drawn much attention in following studies. Tyni and Ylinen (2006) were also interested in optimization of energy consumption using GA. Sorsa et al. (2003) used Genetic Algorithm for optimal control of double-deck elevator group system. To minimize waiting time, Cortes (2004) gave an explicit definition of fitness function and binary encoding scheme for car dispatching. Ghareib (2005) presented a GA based algorithm for minimization of waiting time, regarding initial car states and preload conditions on an explicit scenario. Bolat and Cortes (2011) using binary coding scheme defined another model based on modified fitness functions for journey time optimization. Tartan et al. (2014) introduced an improved algorithm for waiting time optimization in comparison with the algorithm presented by Ghareib (2005) and conventional duplex method on the same scenario .

The main distinction of applications for time parameter optimization lies in the estimation approach of time parameters that will be used in fitness function. Consequently although their definition seem similar, fitness functions implicitly differs from each other according to definition of estimated time parameter. Another characteristic in GA application is encoding problem into chromosome. This is determined by the definition of chromosome structure. Consequently different models can be developed using GA for the same problem. In this study we present an improved car dispatching method for optimization of waiting time that is based on GA. This model combines some properties of previous studies and improves method presented by Tartan et al.(2014) for waiting time optimization. Briefly this method

- Takes into consideration initial car states and preload conditions
- Uses a more compact decimal encoding scheme instead of binary encoding than the referred study
- Improves fitness function for estimated waiting time

2. TIME PARAMETERS and TRAFFIC MODEL

From the perspective of quality of service an efficient EGCS algorithm should dispatch the cars to the registered hall calls minimizing passengers' waiting time. Barney and dos Santos(1985) emphasizes importance of waiting time as the prime psychological constraint. Waiting time is the time starting from hall call registration until a car reaches that floor. Other parameters related to quality of service and hence time, are passenger Average Travel Time (ATT) and passenger Average Journey Time (AJT). Travel time starts from the arrival of the elevator at the floor where passenger is waiting and ends at the arrival at destination floor. As stated by Barney and dos Santos(1985) travel time is secondary psychological constraint for passenger. Estimation of travel time is more complex since the uncertainty due to the dependency on incoming calls and their unknown destinations can significantly affect it. Journey is the total

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time starting from registration of call until reaching destination floor and is calculated as the sum of journey time (JT) and waiting time (WT) (1).

$$JT = WT + TT \quad (1)$$

Although car trip time and journey time can exhibit a correlation with waiting time and decrease in waiting time can be achieved by optimization of these parameters, as shown in example by Tartan et. al (2014) decrease in car trip time does not always result in reducing other time parameters. In this study we directly focus on waiting time aiming to optimize and use it for evaluation of ECGS algorithm's performance.

According to passenger profile, building type and time of the day a dominant traffic pattern can be observed. In particular, during work days high rise commercial buildings exhibit such patterns at different time intervals. In the mornings traffic is upwards from ground floor to office floors and therefore named as up-peak. On the contrary in residential buildings people leaving for work result in a reversed pattern in the mornings and similar pattern can be observed in commercial buildings during work out in evenings. Another specific pattern can be observed at noon is lunch peak. General traffic that includes random upwards calls and downwards calls is named as interfloor traffic. Here instead of specific traffic patterns we consider a more general, random traffic and investigate interfloor focusing on waiting time optimization leaving other constrains.

3. GENETIC ALGORITHM

Genetic Algorithm is an optimization algorithm inspired by natural evolution process. In GA a population consists of individuals each representing a candidate solution for maximization or minimization of a fitness function. The problem is encoded in individuals (also named as chromosomes) as bit strings. For the evolution process towards better generations GA mimics natural selection, mutation and crossover. According to fitness function values fitter individuals have more probability to be selected to take role in producing offspring population. Selected individuals are mated or not according to crossover probability.If a generated random number if lower than crossover probability crossover is applied otherwise pair of chromosomes remain without change. For diversity and global search, with a low probability mutation operator applies mutation. Finally obtained pair of offspring chromosomes take place in new generation. The creation of new chromosomes is repeated until size of new chromosome population becomes equal to size of initial population. Then population is replaced with the new population. The process of generating populations is repeated until the specified maximum number of generations is reached. The flowchart of algorithm is shown in Fig. 1.

In elevator dispatching problem crossover is applied as mutual replacement of genes which are elevator numbers between two individuals. A sample individual is shown in Fig.2.c. When crossover is applied to a pair, after a randomly selected point in chromosome structure elevator numbers assigned to corresponding to hall calls interchange. In mutation for a single individual a randomly selected gene which represents elevator number is changed with another elevator number.

4. PROPOSED METHOD

We propose an elevator dispatching method based on Genetic Algorithm that dispatches cars aiming to minimize average passenger waiting time. Fitness function for GA is defined as

$$f = 1 / T_{av} \quad (2)$$

$$T_{av} = \left(\sum_{i=1}^{K} WT_i \right) / K \quad (3)$$

where K ,WTi and T_{av} representing the number of landing calls, estimated waiting time of call i and average waiting time respectively.

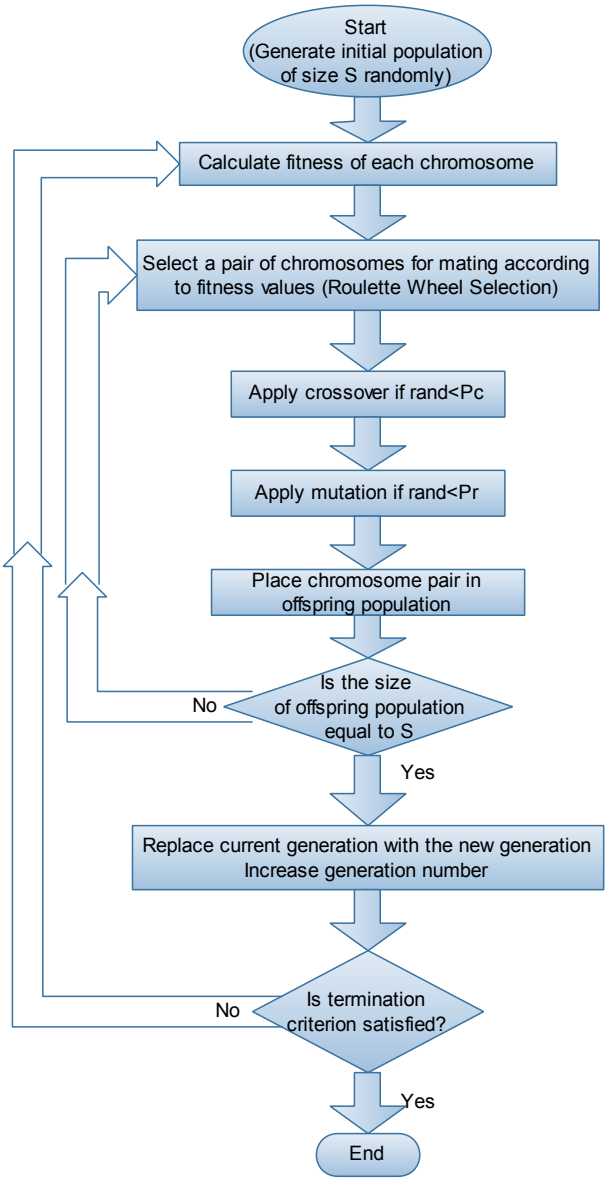

Fig. 1. Genetic Algorithm Flowchart

The input parameters of system which will be used in fitness calculation are given in Table 1. Here we briefly call the sum of door opening time, passenger transfer time and door closing time as the term passive time (PT) since during this interval car stops at a floor. The first four parameters are constants whereas the last three are variables. We use the first six parameters as input parameters of the system. The last parameter is used for calculation of actual waiting times in given scenario to evaluate of the method.

Table 1. System Parameters

NF	Number of floors
NC	Number of cars
pt	Passive Time
it	Inter floor trip time
$HC=[HC_1 ... HC_i ... HC_K]$	Hall call floors
$CF=[CF_1 ... CF_n ... CF_N]$	Car floors
$CDF=[CDF_1 ... CDF_n ..... CDF_N]$	Car destination floors

As stated by Closs (1970) and conventionally can be regarded as passenger habits following common rules are adopted for the system

- A car may not pass a floor at which a passenger wishes to exit.
- The car calls are sequentially served in accordance with the lift trip direction.
- A car carrying passengers cannot change the trip direction if at least one passenger is inside.

4.1 Chromosome Structure

Tartan et. al (2014) following the same scheme presented by Cortes(2004) for encoding car dispatching problem in GA, defined a chromosome as concatenated arrays where each array is representing a car's assignation state to hall calls. In this approach each car's array size is 2x[NumberOfFloors-1] where first part represents upwards calls and second part downwards calls assigned to that car. If a call is assigned to the car it is represented as 1 and 0 otherwise.

In Fig. 2.a. landing call table for a scenario of 10 floors building with 3 elevators is given. Here 1 represents that there is a call and 0 represents there is no call at that floor towards the corresponding direction. A sample chromosome is the concatenation of three rows which are given in Fig. 2.b. However this chromosome structure results in Mx2x[NF-1] bit length which makes it computationally cumbersome where M is the number of cars and NF is the number of floors. Therefore in this study we adapt a compact structure also presented by Bolat et al. (2013) where each gene corresponds to floors at which there exists a call, discarding floors without calls. Each bit value represents the car id assigned to that floor. For demonstration the two chromosome structures representing the same solution are shown in Fig. 2.b. and Fig. 2.c. In this approach chromosome length is variable according to registered calls, but it is more practical instead of binary coding and involving all floors. This approach reduces computational cost in GA by decreasing population matrix from PxMx2x[NF-1] to PxHC where P is number of chromosomes and HC is number of hall calls.

4.2 Estimated Waiting Time Calculation in Objective Function

The crucial part that determines the performance of the method is the approach for estimating waiting time. Jamaluddin et al.(2009) demonstrated the possible routes taken by car as in Fig.3. Route (c) is same as route (d) and route (g) is same as route (h) in terms of calculation formula. Hence we can consider six situations. We discuss these situations under two groups according to car state.

Upwards Landing Calls									Downwards Landing Calls							
F1	F2	F3	F4	F5	F6	F7	F8	F9	F2	F3	F4	F5	F6	F7	F8	F9	F10
0	1	0	1	1	1	0	0	0	0	1	0	1	0	1	0	1	1

(a)

	Upwards Landing Calls									Downwards Landing Calls								
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F2	F3	F4	F5	F6	F7	F8	F9	F10
Car 1	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
Car 2	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0
Car 3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1

(b)

Upwards Landing Calls				Downwards Landing Calls				
F2	F4	F5	F6	F3	F5	F7	F9	F10
1	2	2	1	3	1	2	3	3

(c)

Fig. 2. Problem encoding in GA (a) Landing calls (b) Binary coding (c) Decimal coding

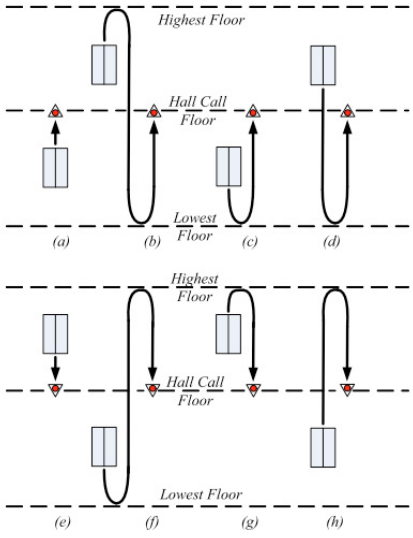

Fig. 3. The different routes taken by a car to reach the hall call floor. (a)–(d) for up hall call, whereas (e)–(h) for down hall call [Jamaluddin et al.,2009]

If car is stopped or going up estimated waiting time of *i*th hall call WT_i is calculated as in (4). Here *n* is the car number assigned to *i*th hall call. As seen from (4) the position of the car CF_n , relative to the hall call position HC_i and hall call direction determines the calculation. Formulas in (4) correspond to Fig.3 (a), (b) and (g-h) where there are one, two and three segments respectively.

$$T_i=\begin{cases}[HC_i-CF_n].it+NS_i.pt & ;\uparrow HC_i \geq CF_n \\ [(NF-CF_n)+(NF-HC_i)].it+NS_i.pt & ;\downarrow HC_i \\ [(NF-CF_n)+(NF-1)+(HC_i-1)].it+NS_i.pt; & \uparrow HC_i < CF_n\end{cases} \quad (4)$$

If car is going down, the calculation is in reverse manner as given by (5). Formulas in (5) correspond to Fig.3 (e), (c-d) and (f) where there are one, two and three segments respectively.

$$T_i=\begin{cases}[CF_n-HC_i].it+NS_i.pt & ;\uparrow HC_i \geq CF_n \\ [(CF_n-1)+(HC_i-1)].it+NS_i.pt & ;\downarrow HC_i \\ [(CF_n-1)+(NF-1)+(NF-HC_i)].it+NS_i.pt; & \uparrow HC_i < CF_n\end{cases} \quad (5)$$

Here NS_i is the minimum number of stops between hall call floor and car floor assigned to that call. Particularly car calls are registered and hence in preload conditions car destination floors are known. For a candidate solution in GA, by considering hall call floors assigned to that car NS_i can be found. In conventional systems only up and down direction buttons are available and hall call destinations are not known. Therefore we call NS_i as the minimum number of stops because a hall call destination may be before the car reaches to HC_i. Nevertheless taking NS_i into account as in (4) and (5) can significantly improve the performance as stated by Tartan et. al (2014), since passive time is a considerable duration in waiting time.

In a candidate solution we can be sure about the end point of the car route in the first segment, if no hall call at the same direction is assigned to that car. If the car is going up it is the highest of the car destinations and the hall call floors assigned to the car in the reverse direction. Similarly if the car is going down it is the lowest of the car destinations and up hall calls assigned to the car. To improve the referred study we take this knowledge into account by checking car assignments. Therefore we check the first conditions in (4) and (5) and extend them by adding an option. If no hall call at the car direction is assigned to the car, after leaving the passenger who is inside, it can take a passenger in the reverse direction. This does not violate accepted rules. Then new extensions for the first conditions in (4) and (5) become as (6) and (7) respectively. If car is going up or stopped and if no up hall call is assigned to it waiting time for hall calls assigned to this car is calculated as in (6).

$$T_i=[(\downarrow HC_{max}-CF_n)+(\downarrow HC_{max}-HC_i)].it+NS_i.pt \quad \text{if all} \downarrow HC<CD_n \ \downarrow HC_{max}=CDF_{n(max)} \quad (6)$$

If car is going down and if no up hall call is assigned to it waiting time for hall calls assigned to this car is calculated as in (6).

$$T_i=[(CF_n-\uparrow HC_{min})+(HC_i-\uparrow HC_{min})].it+NS_i.pt \quad \text{if all} \uparrow HC>CD_n \ \uparrow HC_{min}=CDF_{n(min)} \quad (7)$$

This additional conditions are illustrated in Fig. 4.

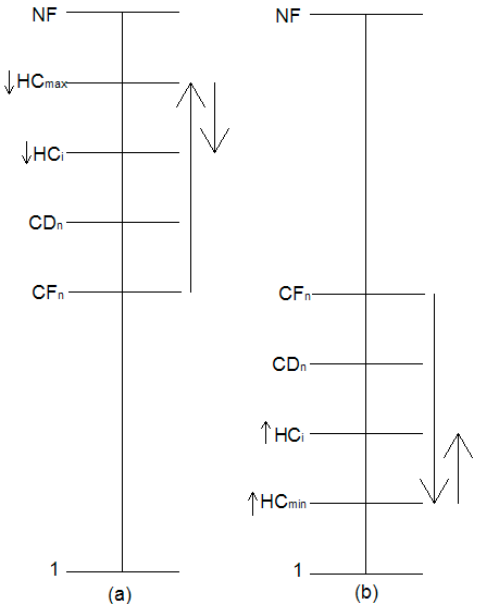

Fig.4. Considered additional cases in GA2

5. SIMULATIONS

In 10 simulations we considered a 20 floor building with 4 cars. Among the simulations average improvement of %21 in waiting time is observed in comparison with compared algorithm. For the purpose of comparison and demonstration we pick a sample scenario given by Ghareib (2005) where conventional duplex algorithm (Otis,1991) was also used for comparison. We consider that visualization of the scenario can explicitly reflect the idea behind the algoirthm that yields better waiting time. Besides we compare the proposed method with the method in the referred study (Tartan et.al,2014) that uses (4) and (5), naming it as GA1. The proposed method is named as GA2.

Table 2. Time constants

Parameter	Duration (sec.)
Inter floor trip time	2
Door opening time	2
Passenger transfer time	3
Door closing time	2
Passive time	7

Table 3. Hall call floors, directions and destinations

Hall Call	Direction	Destination
H7	Down	1
H9	Up	16
H11	Down	2
H12	Up	20
H13	Down	6
H15	Down	9

In GA population size is set as 50 and maximum number of generations is set as 100.Crossover probability is 0.7 and mutation probability is 0.01. Accepted time constants are given in Table 2.These parameters ensure the convergence in all 10 simulations. However for the sake of computational cost maximum generation number and population size can be further investigated. In the sample scenario hall calls and initial conditions of cars are given in Table 3 and Table 4, respectively.

Table 4. Car states

Car	Car Floor	Direction	Destination
Car1	5	Up	7
Car2	17	Down	8
Car3	3	Up	18,20
Car4	19	Down	1,6

In this specific example proposed method yields three equivalent solutions in terms of average estimated waiting times. Assigned hall calls of three solutions by the proposed method with solutions of GA1 and conventional method are given in Table 5.

Table 5. Car dispatching table

Algorithm / Car	Car1	Car 2	Car3	Car4
Conventional Algorithm	H_9,H_{12}	H_7,H_{11}, H_{13},H_{15}	-	-
GA1	H_{12}	$H_{11, 15}$	H_9	H_7,H_{13}
GA2 (solution 1)	H_7	H_{11},H_{15}	H_9,H_{12}	H_{13}
GA2 (solution 2)	H_7	H_{11},H_{13}	H_9,H_{12}	H_{15}
GA2 (solution 3)	H_7	H_{13},H_{15}	H_9,H_{12}	H_{11}

Table 6. Actual waiting time

Algorithm / Car	H7	H9	H11	H12	H13	H15	Total
Conventional Algorithm	55	15	26	28	15	4	143
GA1	31	12	19	21	12	4	99
GA2 (solution 1)	4	12	19	25	12	4	76
GA2 (solution 2)	4	12	19	25	8	8	76
GA2 (solution 3)	4	12	16	25	15	4	76

Although in this particular example three actual waiting times are also equal as in the case of estimated waiting times, this could not be if a hall call destination was before the subsequent hall call. If such a destination floor existed passive time at this stop would affect actual waiting times. On the other hand, since destination floors of hall calls cannot be known a priori, algorithm could still yield same solutions by estimation. Nevertheless the average waiting time provided by GA2 will be less or equal to GA1, because it covers all cases as in GA1 and moreover exploit the knowledge by considering subcases. The actual number of stops and car trip time are also given in Table 7 and Table 8, respectively. It should be noted that car trip time and number of stops were not point of interest. Although number of stops and car trip time also depend on incoming passengers' destinations, by using minimum number of stops a weighted output to balance number of stops can be used in accordance with estimated waiting times.

Table 7. Number of car stops

Algorithm / Car	Car1	Car 2	Car3	Car4
Conventional Algorithm	5	9	2	2
GA1	3	5	4	4
GA2 (solution 1)	2	5	5	3
GA2 (solution 2)	2	5	5	4
GA2 (solution 3)	2	5	5	4

Table 8. Car trip time

Algorithm / Car	Car1	Car2	Car3	Car4	Total
Conventional Algorithm	65	95	48	50	258
GA1	51	65	62	64	242
GA2 (sol.1)	30	65	69	57	221
GA2 (sol. 2)	30	65	69	64	228
GA2 (sol. 3)	30	57	69	64	220

6. CONCLUSIONS

In this study we proposed an improved version of GA based method for waiting time optimization in ECGS. The proposed method not only reduces average waiting time but also uses a simpler problem encoding approach which is more suitable for implementation. Scalability issue for different number of floors and cars is beyond the scope of this study. This issue will be addressed with another important issue which is car trip time and will be investigated in future study.

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