# Vehicle Scheduling of Public Transport Considering Passenger Behavior 

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#### Abstract

Public transport is a vital part of the whole urban transportation. There are more than 1100 bus routes, over $\mathbf{1 2 , 0 0 0}$ buses for scheduling in Chengdu, China. For balancing interests of the passengers and bus companies, this paper chooses fast bus as the study object, addresses a public transport dispatch problem with the objective of minimizing average waiting time and optimize passenger satisfaction at the same time. Following the research line, we apply prospect theory to analyze passenger behavior integrating with fuzzy theory and construct satisfaction function. For a multi-objective mathematical model combined with the constraints and it being a NP-hard problem, a plant growth simulation algorithm is proposed. Ultimately, verify feasibility and validity of the model and algorithm by simulating real example. Computational experiments show that the two objectives can be achieved effectively through a rational scheduling for public transport vehicle scheduling.


## Keywords

Public Transportation; Optimization; Scheduling; Prospect Theory; Passenger Behavior.

## 1. Introduction

With a rapid development of modern social economy and urbanization demands for a high efficiency and low consumption urban public transportation become larger and larger. And the daily passenger volume (2020) are over 10.92 million passengers. As a core of the whole urban transportation, a rational scheduling in bus operation can not only benefit people who choose to go out by bus, furthermore, it may also be helpful to solve traffic jam and even environmental pollution in modern city. Besides it's a complex dispatch system whose scheduling environment is equivalent to a flexible job shop, which consists of various features, such as .the dynamic travel time, different bus departure interval and peak hours. Aiming at those features, this paper attempts to promote the efficiency of transportation by adding fast buses and docking sites and setting the number and departure interval of the fast bus reasonably.
This paper focuses on the operation of bus scheduling optimization problem and makes contributions as follows: one is to combine with real situation and behavior science theory to analyze behavioral characteristics of passengers who are under three aspects; resources and environment, constraints and objective function class. Secondly different people who have the same waiting time may have different psychological perception so that we integrate the fuzzy theory into prospect theory, and build perceived satisfaction function which is related to the passengers' waiting time, furthermore use plant growth simulation algorithm to achieve the optimal scheduling. Finally numerical simulation of the practical data has been conducted to verify the feasibility and effectiveness of the research.
The vehicle scheduling problem in public transport system can be defined as a non-identical parallel machine scheduling with restriction of machine eligibility constraints. This kind of NP-hard class
problem has caused an increased enthusiasm from the research community that heavily skews towards the application of heuristics algorithms, mainly including ant Colony algorithm hybridized with insertion heuristics [1]; genetic algorithms and artificial neural networks [2]; simulated annealing algorithm [3];meta-heuristic algorithms [4];approximation algorithm [5];polynomial time approximation algorithm [6]; Razali [7] introduced An Efficient Genetic Algorithm for Large Scale Vehicle Routing Problem Subject to Precedence Constraints; Larsson et al. [8] presented heuristics and compare their performance with the optimal solutions on the German Autobahn road network. Polat et al. [9] developed a perturbation based neighborhood search algorithm combined with the classic savings heuristic, variable neighborhood search and a perturbation mechanism. Nagatani [10] thought that the motion of shuttle buses is depended on the inflow rate and presented the nonlinearmap model for the dynamics of shuttle buses. With the consideration of many emergency events which may affect vehicle arrivals, Haghani et al.[11] presented multiple depot and two single depot vehicle scheduling models. Hassold and Avishai [12] proposed a new methodology based on a minimum-cost network flow model, and utilized sets of Pareto-optimal timetables for individual bus lines. Visentini et al. [13] focused on real-time schedule recovery in the occurrence of one or several severe disruptions such as vehicle breakdowns, accidents and delays. He [14] proposed a scheduling model by using accurate and reliable information to deal with bus bunching problems, and determine the actual outbound time and bus cruising speed. Marković et al. [15] reported on a system developed to address the dial-a-ride problem and an implementation for Maryland.
Fore-mentioned literature has made a significant exploration on the optimization of vehicle operation scheduling. However, classical scheduling problems all rested on the hypothesis of complete rationality. In fact, modern public transport dispatching not only has features of non-identical parallel machine, but it's also a contains passenger participation, and passenger behavior research is also a critical part in the Operational Management(OM).As a new research field, behavioral science has both taken psychological factor and organizational behaviors factors into traditional operational area. In this study, we are going to establish an optimized model which takes passenger perception into consideration. Xu et al. [16] analyzed bus scheduling problem and the characteristic periods were divided by using the ordered samples clustering of travel time based on vehicle real-time GPS data. Shui et al. [17] proposed a clonal selection algorithm to quickly generate satisfactory solutions for large-scale bus scheduling problems. Ibarra-Rojas et al. [18] develop a complete integration of timetabling (TT) and vehicle scheduling (VS) problems, in the TT problem they try to maximize the number of passengers benefited by well-timed transfers, while in the VS problem they seek to minimize the operating costs, which are related to the fleet size.
Prospect theory created in 1979 and developed in 1992 by Kahneman and Tversky[19,20].The theory states that people make decisions based on the potential value of losses and gains rather than the final outcome, and that people evaluate these losses and gains using certain heuristics. Recent years, many studies related to the application of prospect theory. For instance, Hjorth and Fosgerau [21] established a diminishing or constant sensitivity of value functions based on the prospect theory. Liu et al.[22] presented some preliminary discussions of applicability of prospect theory on a use-oriented product service system-vehicle sharing service. Zhou et al. [23] applied the prospect theory to analyze the characteristics of drivers' route choice behavior. Liu and Fan et al. [24] proposed a risk decision analysis method based on CPT to solve the risk decision-making problem in emergency response. Xu et al. [25] developed a general travel decision-making rule utilizing cumulative prospect theory (CPT) that investigates the mechanism of travelers' behavior. CPT is a revised version of prospect theory.
On the basis of research proposed, this study proposes a non-identical parallel machine problem in public transport system considering passenger satisfaction on the basis of behavioral science theory. The remainder of the paper is organized in five sections. In section 2, we build scheduling model based on the analysis of passenger behavioral characteristics and establish perceived satisfaction function; in section 3,the scheduling problem is described in detail by a triplet $\alpha / \beta / \gamma$, then construct a multi-objective scheduling model; in section 4,this study adopts plant growth simulation
algorithm to solve the problem; section 5 is computational experiments ;the conclusions of the paper are stated in section 6 .

## 2. Problem Statement

### 2.1 Passenger Behavioral Analysis

Bus operating system is a typical service organization including passengers, bus enterprise managers, driver conductors (of a public vehicle) and other behavioral agents. Enterprises should not only attach importance to benefit but also focus on human factors. Assuming the passenger as the major behavioral agent, it's significant to try to enhance passengers' satisfaction when analyzing the vehicle scheduling problem. This paper attempts to combine with realistic situations and behavioral science theory to analyze passenger behavioral characteristics. Passengers' behaviors are affected by the following factors:
Self-interested behavior: In rush hours, passengers on the bus do not want to go to the back of the bus in order to get off conveniently, thus the middle of a bus gets more crowded, ultimately it is too crowded to get on the bus for the rest of waiting passengers. Self-interested behaviors cause part of passengers wait a longer time and form a disturbance of waiting time .we define $r_{1}$ as the disturbance factor of waiting time.
Human mental delay: with more passengers, the more crowed the bus will be. On the one hand, the average boarding time when passengers squeeze into the bus is more than the time in line. On the other hand, when the passengers get off, for the human mental delay, some passengers not walk to the back door beforehand unless the bus stopped. Hence the time vehicle docking sites will get longer. We define $r_{2}$ as the disturbance factor of the vehicle stop time.
Riding comfort: With the improvement of people's living standard and the transport network, more requirements for riding comfort are demanded. In this paper riding comfort is measured by the degree of congestion [26]. That means we will determine a maximum of bus passenger capacity and maintain some sparsity in the bus to ensure passengers' riding comfort. We assume that bus passenger capacity does not exceed 1.2 times the rated capacity. And we define $\sigma$ as the rated capacity.
Bus selection: Passengers will choose a different travel period and sites according to their purpose of travel and travel habits. Since the choice of passengers' traveling time is different, traffic will form "peak" and "low" periods. Even in the same site, different choice will form a large traffic site or smaller traffic site. Particularly when we go to work in the morning, it is easy to cause traffic congestion.
Waiting time: when passengers choose a site, they will estimate waiting time of the current site. When the actual waiting time is less than the estimated, their satisfaction is high denoted gains. But with the waiting time increasing, the gain will decrease. When the actual waiting time is more than the estimated, their satisfaction is declining and denoted losses. When passengers' waiting time gets much longer, more and more passengers arrive at the stop. at this time their satisfaction marginally decreases. If passengers' waiting time is so long that exceeds passengers' limitation, they will be agitated and irritable even change their traveling style or cause other negative behaviors. As time goes by, part of passengers may give up the trip mode. This paper tries to utilize value function in prospect theory to describe this kind of behavior, and perceived satisfaction with maximizing passengers' perceived satisfaction as the objective function.

### 2.2 Establishing Perceived Satisfaction Function

Passengers mainly concern about waiting time. Therefore, the key of the decision-making is to improve passengers' perception satisfaction of waiting time. The perception is the result of people's subjective feelings and cognition, and is based on the non-complete rationality of passengers. In this paper, passengers' behavioral characteristics are analyzed in the framework of prospect theory. People usually reflect the risk aversion when people face up to the relative certainty of earnings and
the relative uncertainty of the risk, but confront the relative uncertainty of loss decision making or the relative certainty of losses always reflecting the risk pursuit. For this feature we construct value function to describe individual behavior instead of choosing utility function. The value function that passes through the reference point is s-shaped and asymmetrical. Losses hurt more than gains feel good (loss aversion). This differs from expected utility theory, in which a rational agent is indifferent to the reference point. In expected utility theory, the individual only cares about absolute wealth, not relative wealth in any given situation.
For one thing, prospect theory is a descriptive decision analysis model developed in behavioral science and psychology, has a unique advantage in describing human behavioral characteristics. But we can't measure the behaviors of the uncertainty with prospect theory for the lack of mathematical theory support. On the contrary, fuzzy theory can mathematically depict the uncertainty of human behavior, but not accurately describe the behavioral characteristics of people. Based on this, the fuzzy theory is integrated into prospect theory. We employ the fuzzy membership function to portray the uncertainty of human behavior mathematically and establish perceived satisfaction function of passengers' waiting time.

### 2.2.1 Value Function based on Prospect Theory

The length of waiting time is a major concern of passengers. According to the prospect theory, each passenger would set a reference point and then compute a subjective value (utility) of satisfaction , based on the potential outcomes and their respective probabilities, and then choose the alternative having a higher utility. And people's different sensitivity to loss and gain is described. Value function model as equation(1):

$$
v(x)= \begin{cases}(x)^{\alpha} & \text { if } x \geq 0  \tag{1}\\ -\lambda \cdot(-x)^{\beta} & \text { if } x<0\end{cases}
$$

$\alpha$ and $\beta$ are estimable coefficients, which determine the concavity and the convexity of the function respectively, $\alpha<1, \beta<1$. $\lambda$ is the parameter of loss aversion, which means the perceived value is steeper in the loss domain than that in a gain domain. The value function is defined on deviations from a reference point and is normally concave for gains (implying risk aversion), commonly convex for losses (risk seeking) and is generally steeper for losses than for gains (loss aversion). The graphic illustration of the Prospect Theory is showing as Fig.1:


Fig. 1 Graphical illustration of the Prospect Theory

### 2.2.2 Selecting Reference Point

In line with the prospect theory, the subjective feeling of passengers is signified by the value function which is core content in this theory. At the initial stage, decision makers will set a reference point
where value is 0 , people judge their gains or losses based on this reference point, thus the selection of the reference point is the core of prospect theory. Generally speaking, if the reference point is different, the same waiting time for passengers at different sites their perception will not be the same. Hence reflecting the individual differences in the choice of optimal allocation scheme is very important in the model. In real life, there is a difference in the objective conditions of the sites, so passengers at different sites their perception benchmark is different. This paper denotes $i$ as the sites, and sets their average waiting time ( $\overline{d_{i j}}$ ) as the passengers' perceptive reference point on site $i$,

$$
\begin{equation*}
\overline{d_{i j}}=\frac{\sum_{j=1}^{n} \sum_{e=1}^{Q_{i(1)}} d_{i j}^{e}}{\sum_{j=1}^{n} Q_{i j(1)}} \tag{2}
\end{equation*}
$$

Where $n$ is the total number of executions transport task during peak traffic; $j$ denotes the any one of transport tasks, each transport task $j \in[1, \mathrm{n}] ; \overline{d_{i j}}$ indicates passengers' average waiting time on site $i ; e$ signifies a passenger; $d_{i j}^{e}$ expresses the actual waiting time of passenger $e$ on site $i$ transport task $j ; Q_{i j(1)}$ denotes the number of passenger getting on the bus on site $i$ transport task $j$.

### 2.2.3 Analysis of Passengers' Perception Waiting Time

Set passengers' average waiting time $\left(\overline{d_{i j}}\right)$ as the reference point, and let the value of cardinality of perceived waiting time as 0 . Based on the prospect theory, if $d_{i j}^{e}<\overline{d_{i j}}$, passengers wait from 0 on one site whose perceived satisfaction is high and reflects gains. With $d_{i j}^{e}$ approaching to $\overline{d_{i j}}$, perceived satisfaction decreased. Passengers' perceived satisfaction reflects losses and drop rapidly when $d_{i j}^{e}$ $>\overline{d_{i j}}$. And there is an extreme value denoted $R^{e}$, the closer the extreme value, the number passengers, and finally perception satisfaction flattens out. Accordingly set the actual waiting time of passengers $d_{i j}^{e}$ as X-axis, the passenger waiting time perceived satisfaction $S\left(d_{i j}^{e}\right)$ as Y-axis, and satisfaction curve of passengers' perceived waiting time can be drawn by the prospect theory value function. Substantially see Fig.2:


Fig. 2 Passengers' perceived satisfaction curve

### 2.2.4 Determining Passengers' Perceived Satisfaction Function

Compared Fig 2 and Fig 1we can find that Fig. 2 can be roughly obtained by the symmetry about the y-axis of Fig 1 moved $\overline{d_{i j}}$ toward the right. In Fig.2, curve in the second quadrant of coordinate represents a decreasing of passengers' satisfaction, and 0 is the lower limit. Curve in the fourth quadrant of coordinate denotes decline too, and when $d_{i j}^{e}$ reaches to $R^{e}$, passengers' satisfaction decreases to the lower limit in this quadrant. What's more, passengers' perceived time is fuzzy, for example, actual waiting time, waiting time border and so on, so this paper adopts the method of fuzzy processing time to describe passengers' actual perception, meanwhile defines passengers' perceived satisfaction as fuzzy membership function of their waiting time. Membership is 1 . Function model is shown as equation(3) :

$$
S\left(d_{i j}^{e}\right)= \begin{cases}\left(\frac{\overline{d_{i j}}-d_{i j}^{e}}{\overline{d_{i j}}-0}\right)^{\alpha} & \text { if } 0<d_{i j}^{e}<\overline{d_{i j}}  \tag{3}\\ -\lambda\left(d_{i j}^{e}-\overline{d_{i j}}\right)^{\beta} & \text { if } \overline{d_{i j}} \leq d_{i j}^{e}<R^{e} \\ -1 & \text { if } R^{e} \leq d_{i j}^{e}\end{cases}
$$

Here, $R^{e}=\overline{d_{i j}}+\left(\frac{1}{\lambda}\right)^{\beta^{-1}}, R^{e}$ is the border of passengers' waiting time, if their waiting time exceeds $R^{e}$, passengers will give up the bus, and satisfaction is -1 .

## 3. Problem Description and Model Building

### 3.1 Problem Description

As a typical scheduling problem which contains passengers, it's important to make a deep research on passenger behaviors in the public transport dispatching. On the background of practical case, we emphasize analyzing the characteristics of passenger perception combined with behavior science theory in this study, and the public transport vehicle scheduling problem is described by a triple $\alpha / \beta / \gamma$ as follows:

### 3.1.1 Resources and Environment ( $\alpha$ field)

The $\alpha$ field can be equivalent to machines in parallel with non-identical speeds ( Qm ). People may have different choices in bus periods and stations because of different destinations and diverse travel habitats. In fact, the passenger flow volume, such as 'rush hours' or 'low hours', is the result of passenger's choices. Similarity, the passenger flow volume of stations is also depended on passenger's choice of station. In practical scheduling, bus companies mainly add fast buses in rush hours to ease traffic pressure. In this way, the bus only need to stop at high passenger flow stations so that can not only save time but also relief traffic pressure. In this study, we mainly focus on optimized dispatching in rush hours to balance the interests of the bus company and passenger satisfaction. We assume that $m$ is the total number of site on the up-link; $m_{1}$ is the number of large traffic sites, $m_{2}$ is the number of small traffic sites, and $m_{1}+m_{2}=m$. All buses have the same size, type, and a constant speed, and the rated capacity is defined as $\sigma$. A certain number of the buses are docking on the park of the first and last stop on the bus route, $u$ is the total number of bus on the up-link during rush hours and including fast bus and ordinary bus. Fast buses only serve on large traffic sites, and ordinary buses serve on all sites.

### 3.1.2 Constraints and Characteristics of Tasks ( $\beta$ field)

Constraints of the vehicle scheduling problem are as following: machine eligibility restrictions $M_{j}$, self-interested behaviors $r_{1}$, human mental delay $r_{2}$, bus rated capacity $\sigma$, etc, specifically as follows:
(1) Machine eligibility restrictions $M_{j}$

Ordinary buses must stop at every site, but fast buses are required to stop only on large traffic sits, that is, not all buses are capable of processing all sites, so there are machine eligibility restrictions ,and let $M_{j}$ denote them.
(2) Self-interested behavior $r_{1}$

When the bus loads passengers in rush hours, passengers on the bus do not want to go to the rear of bus so that they can get off the bus conveniently. Therefore, the crowding degree of the bus between front door and rear door gets more and more intense, and it is too crowded to get on the bus for the rest of passengers who wait on the stop. Self-interested behaviors cause part of passengers wait a longer time and form a disturbance of waiting time .we define $r_{1}$ as the disturbance factor of waiting time and put it into scheduling model.
(3)Human mental delay $r_{2}$

During the bus stop to carry passengers on stops, The average time when passengers squeeze into the bus is more than the time in line. For the passengers get off, for the human mental delay, there will always be two or three passengers walking to the back door after the bus stop rather than prepare to get off early. Hence the time vehicle docking sites will get longer. We define $r_{2}$ as the disturbance factor of the vehicle stop time, and add it in scheduling model.
(4) Bus rated capacity $\sigma$

With the improvement of people's living standards and the transport network, requirements for riding comfort get more and more essential. This paper measures riding comfort by the degree of congestion. That means we will determine a maximum of bus passenger capacity and maintain some sparsity in the bus to ensure passengers' riding comfort. We assume that bus passenger capacity does not exceed 1.2 times the rated capacity. We define $\sigma$ as the rated capacity, and add it in scheduling model.
(5) During the process of bus operation, all buses have the same route, and on each site all lines are assumed to operate under the First in first out discipline.
3.1.3 Scheduling Objective ( $\gamma$ field)

In vehicle scheduling problems, passenger satisfaction has a direct relationship with the waiting time. In this paper, set $\bar{S}\left(d_{i j}^{e}\right)$ as passengers' average perceived satisfaction of the waiting time, and maximizing $\bar{S}\left(d_{i j}^{e}\right)$ guarantee demands and interests of passengers, and ultimately achieve a balanced optimization of passenger and the bus company interests.

### 3.2 Parameter Design

Let $m$ denote the total number of site on the up-link, $i$ represents any one of these sites, and each site $i \in[1, m] ; n$ is defined as the total number of tasks to perform transportation, $j$ represents any one of these transport tasks, and each transport task $j \in[1, n]$; let $C_{i j}$ denote the departing time on site $i$ transport task $j ; Q$ signifies the total number of passengers during peak hours; $Q_{i j(1)}$ is the number of passenger getting on the bus on site $i$ transport task $j, Q_{i j(2)}$ is the number of passenger getting off the bus on site $i$ transport task $j$.We define $t$ as departure interval between buses during peak hours, $t_{0}$ is the time required to get on and get off per passenger; $s_{0 i}$ is the travel
distance of the bus reaches the site $i ; v$ is the average speed of buses; $t_{i}^{e}$ is arrival time of passenger $e$ on site $i$.

### 3.3 Basic Assumptions

Assumption 1: The arrival time interval on any site follows negative exponential distribution whose parameter is $\lambda_{i}$.

Assumption 2: Buses drive at an equal speed anywhere, the distance between two sites is approximately equivalent.
Assumption 3: Buses can arrive on time during bus process of operation maintaining normal traffic (accidents unconsidered).
Assumption 4: The situation that more than one bus of the same line arrive on one site at the same time does not occur.

### 3.4 Model Building

To sum up, scheduling mathematics model of fast bus as follow:

$$
\begin{gather*}
\text { Maximize } \bar{S}\left(d_{i j}^{e}\right)  \tag{4}\\
\text { Subject to } \bar{S}\left(d_{i j}^{e}\right)=\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{e=1}^{k} Q^{-1} S\left(d_{i j}^{e}\right)  \tag{5}\\
p_{i j}=\max \left(Q_{i j(1)}, Q_{i j(2)}\right) \times t_{0} \times\left(1+r_{2}\right) \times w_{i j}  \tag{6}\\
C_{i j}=\sum_{i=1}^{k} p_{i j}+(j-1) t+s_{0 i} / v  \tag{7}\\
d_{i j}^{e}=\left[C_{i j}-p_{i j}+(e-1) t_{0}-t_{i}^{e}\right] \times\left(1+r_{1}\right)  \tag{8}\\
0.6 \sigma \leq \sum_{i=1}^{k}\left(Q_{i j(1)}-Q_{i j(2)}\right) \leq 1.2 \sigma  \tag{9}\\
Q=\sum_{j=1}^{n} \sum_{i=1}^{m} Q_{i j(1)} \tag{10}
\end{gather*}
$$

$$
\begin{equation*}
w_{i j} \in\{0,1\} \tag{11}
\end{equation*}
$$

Decision variable ${ }^{w_{i j}}$ is used to characterize the implementation of the tasks, and its value has two cases:

$$
w_{i j}= \begin{cases}0 & \text { fast buses perform task } j, i \notin m_{1} \\ 1 & \text { other situations }\end{cases}
$$

In the above scheduling model, the objective function of vehicle scheduling (4) maximizes passengers' average perceived satisfaction. Equation (5) to (11) are constraints, constraint (5) measures passengers' average perceived satisfaction of the waiting time, constraint (6) ensures the bus dwell time on site ${ }^{i}$ transport task ${ }^{j}$, constraint (7) represents the bus leaving time on site ${ }^{i}$ transport task $j$; constraint (8) measures the actual waiting time of passenger $e_{\text {on site }} i$ transport task ${ }^{j}$; constraint (9) ensures bus passenger capacity is maintained between $60 \%$ and $120 \%$ of rated capacity; the total number of passengers during peak hours is defined by constraint (10); the range of decision variable is given by constraint (11).

## 4. Scheduling Algorithmic Designing

Plant growth simulation algorithm (PGSA) is a bionic intelligent search algorithm based on the process of plant growth. Its parameter is relatively simple and scheduling computing performance is higher. At present, PGSA is mainly used in the field of engineering technology [27], but in the field of transportation network layout and vehicle scheduling is applied less. Algorithm steps are as follows:

### 4.1 The Initial Growing Point

The initial growing node is also called the trunk, and is used for simulating the location point of plant growth. According to the actuality, any departure plan can be seen as a growing point, feasible solution space as the growing node set $\left\{d_{1}, d_{2}, \cdots, d_{l}\right\}$ of the plant system, and the $k$ growing node $d_{k}$ is:

$$
\begin{equation*}
d_{k}=(\cdots, A, \cdots, B) \tag{12}
\end{equation*}
$$

A and B represent any ordinary vehicle and any fast vehicle, respectively, in the initial growing node set, quantity of fast vehicle each growing node inside is set to 1 .

### 4.2 Morphactin Concentration

Morphactin is a kind of chemical substance existing in plants that can determine which growing node to grow preferentially. Combining scheduling problems, the value of growing node $d_{k}$ corresponds to morphactin concentration $D_{k}$ and its expression is:

$$
\begin{equation*}
D_{k}=\frac{1 / f\left(d_{k}\right)}{\sum\left[1 / f\left(d_{k}\right)\right]} \tag{13}
\end{equation*}
$$

Here $f\left(d_{k}\right)$ is the objective function of scheduling, that means $f\left(d_{k}\right)=\bar{S}\left(d_{i j}^{e}\right)$. In the closed system of multiple cells, the sum of the morphactin concentration values that corresponding to each growing node is 1 , that is $\sum D_{k}=1$. According to the formula (13), the set of growing node corresponding to the set of morphactin concentration $\left\{\mathrm{D}_{1}, \mathrm{D}_{2}, \cdots, \mathrm{D}_{l}\right\}$ is calculated, and to establish the probability space model of the morphactin concentration.

### 4.3 Preferential Growing Point

First, generate random number $(0,1)$ randomly, and named $\alpha$. The random number is within the space that belongs to $D_{1}, D_{2}, \cdots, D_{l}$, and growing node that corresponds to that space will grow preferentially, thereby the growing node of this iteration has been selected.

### 4.4 Generate a New Growing Point

Under the external environment stimulation (such as the light), the preferential growing node will grow and generate new growing nodes in the next step and this repeats till plant is fully grown.The plant growth is modelled as the nodes of the plant that is equivalent to possible solutions. Combined with the reality, new growing nodes are generated by the change of departure interval and the number of fast buses.

### 4.5 Determine the Optimal Growing Node

Compared new growing nodes with iterative growing nodes, retain growing nodes with the optimal scheduling objective function value for next search operation. Stop growing and output the preferential growing node till the set number of iterations is reached and the growing node with highest morphactin concentration is the optimal scheduling scheme.

## 5. Computational Results

An up-link bus line in Chengdu as the simulating real example, first analyze realistic situation to determine the peak hours and big traffic sites of residents traveling, and then MATLAB are used for numerical simulation, finally get the optimized scheduling scheme.

### 5.1 Analyze Realistic Situation

By using the SPSS to analyze the questionnaire survey data, the continuous cumulative probability graph of the residents is shown in Fig . 3


Fig. 3 cumulative probability graph of residents' departure time

Fig .3 shows that the residents' departure time focused on 7:00-8:00, at this period the number of passengers on each site of route are counted. Through investigation, there are 24 sites on the up-link, the whole line is 18.2 km , 26 buses can be put into use on the first site and the average speed is 17.6 $\mathrm{km} / \mathrm{h}$. After field observation and data statistics, we acquire part sites traffic situation on the up-link, as presented in Fig .4:


Fig. 4 passenger flow volume of part sites

By the analysis of data and graphs, the 4th site and7 th, 8 th, 10 th, 12 th, 13 th, 15 th, 16 th, 18 th, 22 th are large traffic sites, so the study sets those sites to fast bus sites.

### 5.2 Determine the Scheduling Scheme

Simulation platform in SAMSUNG at 1000 MHz frequency hardware platform, has been used for simulating the output of our optimization algorithm. In this instance of the model, passengers' arrival rate on large traffic sites obey $[0.10,0.14]$ uniform distribution; the number of outbound passengers subject [13, 28] uniform distribution; passengers' arrival rate on small traffic sites submit [0.02, 0.06] uniform distribution; the number of outbound passengers subject [ 0,10 ] uniform distribution and the number of outbound passengers on last site obey [9-20] uniform distribution. In addition, passenger arrival rate on first site is 0.11 ; the average time required for each passenger on and off is 2.8 seconds; rated capacity of buses is 100 people; he disturbance factors $r_{1}=0.15, r_{2}=0.1$, and three typical values $\alpha=\beta=0.88 \lambda=2.25$. We then utilize the MATLAB software programming setting the number of iterations to 50 times, and run four times in SAMSUNG at 1000 MHz frequency hardware platform, the average running time is 50 seconds. The convergence graph is obtained shown in Fig 5.


Fig. 5 Process convergence graph

In the Fig 5, the ordinate denotes passengers' average perception satisfaction of waiting time, and the abscissa represents the number of iterations. The curve reflects the iterative convergence process of plant growth simulation algorithm in solving bus scheduling problems. The results indicate that passengers' average perception satisfaction increases with the number of total iteration increasing, finally reaching a steady state. Moreover, it shows the convergence and effectiveness of the algorithm. The simulation results also get the bus scheduling scheme, as shown in Table 1.

Table 1. The bus optimization scheduling results

| Peak hours | Current scheme | Optimized scheme |
| :--- | :---: | :---: |
| Fast bus number | 0 | 5 |
| Departure interval | 3.00 | 3.60 |
| Average perception satisfaction | 0.15 | 0.64 |

In Table 1 , departure schemes of bus scheduling optimized before and after are compared. As can be seen, optimized scheme increases by 5 fast buses and sets the departure interval to 3.6 minutes, the passengers' average perception satisfaction of waiting time reached 0.64 in gains status, with respect to the current scheme, the satisfaction improved by 0.49 . Results indicate that using reasonable fast bus scheduling can better improve passengers' average perception satisfaction and achieve a balanced optimization of the interests of both passengers and bus companies.

## 6. Conclusion

Operation scheduling optimization of public vehicles has the great significance in reducing urban traffic accidents, optimizing the traffic environment, improving passenger satisfaction and decreasing the operation cost of the bus companies. Nowadays most scholars have modeled for vehicles scheduling problems considering uncertain factors of real life such as road congestion, vehicle breakdown or traffic accidents and other factors who use intelligence algorithms with high computing performance (such as genetic algorithm, simulated annealing algorithm) to get bus scheduling scheme. This paper studies the fast buses in rush hours, firstly combines with real situations and behavioral science theory to analyze passenger behavioral characteristics. On the basis of that, constructs optimal scheduling model, and then utilizes plant growth simulation algorithm. Ultimately computing result shows that this research achievement can lay the foundation of decision making in improving public travel and the optimization of urban traffic environment. On this basis, how to reflect real life uncertainties in the model, and the realization of coordinated scheduling between needs and interests among passengers, bus companies, drivers and conductors will be the next issue to be studied.

## References

[1] S. R. Balseiro, I. Loiseau, and J. Ramonet. An Ant Colony algorithm hybridized with insertion heuristics for the Time Dependent Vehicle Routing Problem with Time Windows, Computers and Operations Research, vol. 38 (2011), 954-966.
[2] S. Dündar and I. Şahin,I. Train re-scheduling with genetic algorithms and artificial neural networks for single-track railways, Transportation Research part c-Emerging technologies , vol. 27 (2013), 1-15.
[3] A. Khormali, A. Mirzazadeh, and F. Faez. The open shop batch processing problem with non-identical processing times, using simulated annealing and genetic algorithms approaches, International Journal of Advanced Manufacturing Technology, vol. 59 (2012), 1157-1165.
[4] K. Li and S. L.Yang. Non-identical parallel-machine scheduling research with minimizing total weighted completion times: models, relaxations and algorithms, Applied Mathematical Modelling, vol. 33 (2009), 2145-2158.
[5] B. Y. Cheng, S. L. Yang, X. X. Hu, and B. Chen. Minimizing makespan and total completion time for parallel batch processing machines with non-identical job sizes, Applied Mathematical Modelling, vol. 36 (2012), 3161-3167.
[6] J. Q. Wang and J Y.-T. Leung. Scheduling jobs with equal-processing-time on parallel machines with nonidentical capacities to minimize makespan, International Journal of Production Economics, vol. 156 (2014), 325-331.
[7] N. M. Razali. An Efficient Genetic Algorithm for Large Scale Vehicle Routing Problem Subject to Precedence Constraints, Procedia - Social and Behavioral Sciences, vol. 95 (2015), 1922-1931.
[8] E. Larsson, G. Sennton, and J. Larson. The vehicle platooning problem: Computational complexity and heuristics, Transportation Research part c-Emerging technologies , vol. 60 (2015), 258-277.
[9] O. Polat, C. B. Kalayci, O. Kulak, and H. O.Günther. A perturbation based variable neighborhood search heuristic for solving the Vehicle Routing Problem with Simultaneous Pickup and Delivery with Time Limit,". European Journal of Operational Research, vol. 242 (2015), 369-382.
[10]T. Nagatani, "Nonlinear-map model for bus schedule in capacity-controlled transportation. Applied Mathematical Modelling , vol. 37 (2013),1823-1835.
[11] A.Haghani, M. Banihashemi, and K. H.Chiang. A comparative analysis of bus transit vehicle scheduling models, Transportation Research Part b-Methodological, vol. 37 (2003),301-322.
[12] S. Hassold and Ceder. Avishai (Avi). Public transport vehicle scheduling featuring multiple vehicle types, Transportation Research Part b-Methodological, vol. 67 (2014), 129-143.
[13]M.S.Visentini, D. Borenstein, J.Q. Li, and P.B. Mirchandani. Review of real-time vehicle schedule recovery methods in transportation services , Journal of Scheduling, vol. 17 (2014), 541-567.
[14]S.X.He. An anti-bunching strategy to improve bus schedule and headway reliability by making use of the available accurate information, Computers \& Industrial Engineering, vol. 85 (2015), 17-32.
[15]N. Marković, R. Nair, P.,Schonfeld, E. Miller-Hooks, and M. Mohebbi. Optimizing dial-a-ride services in Maryland: Benefits of computerized routing and scheduling," Transportation Research part cEmerging technologies , vol. 55 (2015), 156-165.
[16]Z. C.Xu, P. J.He, J. Teng, and L. P. Li. Transit Vehicles Intelligent Scheduling Optimization Based on the Division of Characteristic Periods, Procedia - Social and Behavioral Sciences, vol. 96 (2013), 15021512.
[17]X. G. Shui, X.Q. Zuo, C. Chen, and Alice E. Smith. A clonal selection algorithm for urban bus vehicle scheduling, Applied Soft Computing, vol. 36 (2015), 36-44.
[18]O. J. Ibarra-Rojas, R. Giesen, and Y. A. Rios-Solis. An integrated approach for timetabling and vehicle scheduling problems to analyze the trade-off between level of service and operating costs of transit networks, Transportation Research Part b-Methodological, vol. 70 (2014), 35-46.
[19]D. Kahneman and A.Tversky. Prospect theory: An analysis of decision under risk, Econometrica, vol . 47 (1979), 263-291.
[20]D. Kahneman and A.Tversky. Choices, Values, and Frames ,[M]. New York: Cambridge University Press, 2000.
[21]K.Hjorth and M. Fosgerau. Using prospect theory to investigate the low marginal value of travel time for small time changes, Transportation Research Part b-Methodological, vol. 46 (2012), 917-932.
[22] A. Liu, T. Wuest, W. Wei, and S. Lu. Application of Prospect Theory on Car Sharing Product Service System, Procedia CIRP, vol. 16 (2014),350-355.
[23]L.Z.Zhou, S.Q.Zhong, S.F.Ma, and N. Jia. Prospect theory based estimation of drivers' risk attitudes in route choice behaviors, Accident Analysis and Prevention, vol. 73 (2014), 1-11.
[24] Y. Liu, Z.P.Fan, and Y. Zhang. Risk decision analysis in emergency response: A method based on cumulative prospect theory, Computers and Operations Research, vol. 42 (2014), 75-82.
[25]H. L. Xu, J. Zhou, and W. Xu. A decision-making rule for modeling travelers' route choice behavior based on cumulative prospect theory, Transportation Research part c-Emerging technologies, vol. 19 (2011), 218-228.
[26] A. J. Pel, N. H. Bel, and M. Pieters. Including passengers' response to crowding in the Dutch national train passenger assignment model, Transportation Research Part A-Policy and Practice, vol. 66 (2014), 111-126.
[27]R. Srinivasas Rao, S.V. L. Narasimham,and M. Ramalingaraju. Optimal capacitor placement in a radial distribution system using Plant Growth Simulation Algorithm," International Journal of Electrical Power \& Energy Systems, vol. 33 (2011), 1133-1139.

