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A New Framework of Intelligent Public Transportation System Based on the Internet of Things

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ABSTRACT As a new paradigm of information technology, the Internet of Things (IoT) is attracting increasing attention from various industrial fields. It is foreseeable that the applications of IoT will be prevalent in the public transportation system and bring changes to the system in the near future. In this paper, we analyze the impact of IoT environment on the public transportation system, propose a new framework of the intelligent public transportation system based on IoT, and present the deployment of the elements, the communication network, and the three-tier architecture of the system in detail. We also present the information flow, technical scheme, optimization model, and algorithm of the main modules of dynamic optimization of the system. The innovative points of this paper lie in: (1) a new framework for public transport system based on IoT, which integrates the scheduling problems of subway, bus, and shared taxi, is proposed for better-coordinated transfer solutions; (2) transport flow prediction methods based on periodic patterns mining is proposed for road flow analysis and passenger flow analysis, and; (3) mathematical model and DSS-based evolutionary computation algorithm are proposed for solving the dynamic bus scheduling and controlling problems. The proposed intelligent transport system based on IoT can assist the decision makers to increase the utilization rate of the transport resources, improve the efficiency of scheduling, and reduce passengers' traveling time.

INDEX TERMS Public transportation system, dynamic scheduling, traffic flow, the Internet of Things.

I. INTRODUCTION

Nowadays the rapid economic growth of modern cities also causes many serious problems; one of them is traffic congestion. In Beijing, capital of China, people waste over three hours each day stuck in traffic in work days [1]. Even for middle size cities in many developing counties, traffic congestion has become a very common phenomenon. Although government has put a lot of effort to widen the road and increase the investment of the transportation infrastructure, little effects have been made because of the fast growing demand of private cars from citizens.

The only solution available to solve the problem of traffic congestion for middle or large size cities is to develop efficient public transportation. Compared with private cars, vehicles for public transportation can provide much larger loading capacities and are capable of sharing spaces with passengers. The average road area occupied by a passenger of a public vehicle is much less that of a private car. As a positive example, Hong Kong has a large number of populations and also has high density of population, but seldom has traffic congestion because of the well-developed public transport systems. Moreover, public transportation also has many advantages such as low cost, low carbon emissions and less air pollution.

In the past several decades, public transportation system has made a lot of progress with the development of information technology. However, one of the major challenges of the public transportation system is that there are various disturbances and uncertainties [2]. For example,

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many uncontrollable events or variations, such as extreme weathers, fluctuation of passenger flows, breaking down of vehicles, dynamic changes in traffic conditions, may generate discords and difficulties in controlling and managing process of the system, lead to the implementation failure of the predetermined scheduling plans and resource allocation plans. Therefore, new information technologies, operation research methods and advanced management theories are required to be introduced and applied in to the public transportation system to overcome these difficulties.

The internet of things (IoT) provides windows of opportunity for public transportation system. As is well-known, IoT is a new paradigm of information technology based on internet and wireless tele-communication. Components in IoT have unique identities, and they can interact and cooperate with each other to reach common goals. IoT plays an important role in many industrial fields such as manufacturing, logistics, transportation, health care, and will bring a revolutionary change to our daily life [3]. Under the context of IoT, various types of real time information can be obtained for public transportation system, which is very useful for reducing the uncertainty of the system and increasing the system ability of quick response, and will help to precise control and manage of the public transportation system. Another benefit brought by IoT is that, some sub-system of transportation based on IoT has the ability of self-coordination and self-autonomy, which can reduce the quantity of data transmission and alleviate the computational burden of the transit control center. For example, a smart traffic light controller perceives the approaches of buses at a cross-road, and adjusts the times of traffic signal phases. An automatic passenger counter on a bus perceives the existence of passengers, computes the number of passengers by using its embedded identification algorithm, and sends the counting results to the terminal box of the bus. Therefore, under the environment of IoT, public transportation system can provide better control strategies and scheduling schemes, thus can more efficiently utilize the transportation resources and improve the quality of public transportation.

In this paper, we propose a new framework of intelligent public transport system based on IoT. Compared to the existing literature papers related to IoT based public transport system (which are reviewed in Section 2), the innovative points of this paper are given as follows: 1) a new framework model for public transport based on IoT, which integrates the scheduling problems of subway, bus and shared taxi, is proposed for better coordinated transfer solutions; 2) transport flow prediction methods based on periodic patterns mining is presented for road flow analysis and passenger flow analysis; 3) mathematical model and DSS-based evolutionary computation algorithm with multiple planning horizons is developed for solving the dynamic vehicle scheduling and controlling problems.

The rest of this paper is organized as follows. Section 2 briefly reviews the related research papers on this topic. Section 3 proposes the framework of the public transportation system based on IoT. Section 4 describes the design of modules of the dynamic scheduling and controlling system as a kernel part of the whole system. Section 5 proposes the mathematical model and solving algorithms for the dynamic bus scheduling problem. Section 6 presents the case study and experiments for evaluating the algorithms. Finally, conclusions are drawn in Section 7.

II. RELATED WORKS

Public transport system is an essential part of the city transportation and it satisfies the basic travel demand of citizens. In recent years, great interest has been given in public transport system and a lot of research papers have been published around this topic. Definitions, classifications and discussions of the recent advance of public transport system can be found in the survey papers by [4]–[6].

Although IoT is a relatively new concept, many scholars have tried to integrate IoT elements into public transport system. In the follows, we briefly review their research work. Li et al. discussed the necessities of providing a series of public transport services, such as vehicle rescue, video surveillance and control, route optimization, to bus passengers by using RFID and some other technologies related to IoT [7]. Kyriazis et al. presented IoT applications of cruising control for public transportation, which aims at utilizing different resources such as environmental and traffic sensors to provide driving recommendations that aim at eco efficiency [8]. Zhang and Chen proposed a real-time broadcast system about the crowding index in public transport based on IoT, and their system can be used to evaluation crowding status of public vehicles on the basis of wireless sensor network node, sink node and terminal analysis modules [9]. Zheng et al. introduced a newly developed intelligent public transport system with some application of IoT technologies in Chengdu city, and analyzed the performance of the system [10]. Du and Chen presented the design of an emergency management system for public road transport networks, which utilizes IoT technologies for monitoring traffics and critical transport infrastructures in road networks and employs geographic information system (GIS) to facilitate situational awareness and emergency operations [11]. Leite Bastos and Pessoa Albini proposed a new physical infrastructure consisting of cables, sensors and many types of devices to implement IoT based solutions to cover the public transportation system of Curitiba [12]. Sutar et al. presented an approach based on the combination of technologies like GPS and Android as IoT applications which can assuage passengers who commute by the means of public transport [13]. Kang et al. presented the requirements, design and pre-deployment testing of a IoT-based transportation bus as a Mobile Enterprise Sensor Bus (M-ESB) service in China that supports monitoring the urban physical environment and monitoring road conditions [14]. Puiu et al. presented an application for public transport system, which provides route recommendations and incident notifications for the citizens

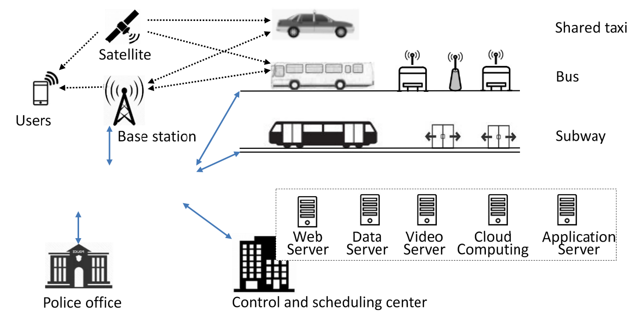

FIGURE 1. Communication network of the intelligent public transport system.

by processing in real-time the IoT data streams about bus arrivals in stations and the incidents reported by citizens [15].

However, the abovementioned research papers did not consider the collaborations among various modes of public transportation from the perspective of information system, did not analyze the impacts and changes brought by the rich data of IoT environment, and did not indicate the central role of the dynamic control and scheduling of public vehicles. These gaps motivate us to carry out this research.

III. DESIGN OF THE PUBLIC TRANSPORTATION SYSTEM BASED ON IOT

Public transportation involves aviation, rail, road and water transport from the broad sense. In this paper, bus, subway (or light rail) and shared taxi, which are the three most commonly used trip choices for citizens in a modern city, are considered in design of the road public transportation system. The communication network of the proposed intelligent public transport system is depicted in Figure 1. The detailed explanation of the figure is given as follows.

(1) Passengers of the system connect to the system via the wireless terminals such as smart phones, which can provide the geographical location information by the embedded Global Position System (GPS) modules and Geographic Information System (GIS) software package.

(2) Shared taxis use the smart devices, e.g., On Board Unit (OBU) or smart phone of the driver, to receive the signal from satellite and connect the control and scheduling center via telecommunication wireless network.

(3) Buses have a much powerful OBU, which is capable of sending GPS information to or receiving data from the control and scheduling center via the telecommunication wireless network, and identifying the smart terminals on bus stops or road facilities (e.g., lamp pole) with the help of the short distance wireless communication protocols. The smart terminals include devices collecting the dynamic road traffic status and passenger flow around the bus stops. When a smart terminal detects the approach of a bus, it identifies the Radio Frequency Identification (RFID) tags on the bus, communicates with the OBU of the bus, receives information (e.g., bus status, number of passengers) from the bus OBU and sends the related data to the control and scheduling center. Since the smart terminals install on the bus stops or road facilities can access the internet via local area network which is more reliable, the control and scheduling center can obtain the accurate position of the bus when there are connection failures between bus OBU and satellite (e.g., bus is in tunnel) or failures between bus OBU and base station (e.g., wireless signal loss).

(4) Subway vehicles and facilities at subway stations are equipped with sensors and devices connected to the control and scheduling center via private network, which is quite reliable.

(5) Control and scheduling center receives data from the sub systems of shared taxi, bus and subway, obtains information from passengers or potential users for further analyzing of origin-destination trip flow, provides the coordinated solutions and sends instructions to the vehicles. The control and scheduling center is deployed with web server, which provides travel query service for end users; data server, which stores the running data of the system; video server, which saves the historical surveillance records of cameras on public vehicles; cloud computing server, which runs the algorithms for scheduling and controlling; and application server, which provide various software applications for the system.

(6) Police office surveils the status of the running public vehicles, acts in case there are police calls or requests from control and scheduling center.

Figure 2 shows the architecture of the Intelligent Public transportation system based on IoT. Generally, the system can be divided into three layers according to the basic concept of IoT, i.e., perception layer, network layer, application layer. The functions and elements of the three layers are explained as follows.

(1) Perception layer: it is the information source of the IoT, and includes various sensors and data collecting devices of the system. To be specific, it can be further divided into: a) devices from passenger, e.g., smart cell phone which can provide location information of passenger and origin-destination of travel plan, bus card which provides the billing and transfer information. b) devices in public vehicles, e.g., the terminal board monitoring the technical parameters (speed, mileage, oil consumption, etc.) of a running bus, fare box for collecting the payment information, smart sensors for detecting the temperature and humidity inside the bus, Automatic Vehicle Location (AVL), Automatic Passenger Counting (APC), digital video camera, etc. c) devices at the bus stop, e.g., smart board for interacting with waiting passengers, Automatic Vehicle Identification (AVI), APC and digital video camera, etc. d) Devices installed on road facilities, e.g., signal device for reporting the real time status of road, smart lamp pole embedded with RFID readers, etc. e) devices used by bus screw, e.g., staff card with RFID tag, mobile device for communicating with control center.

(2) Network layer: it is responsible for transmit the information from perception layer to application layer. It includes the wire communication and wireless communication. The wireless communication can

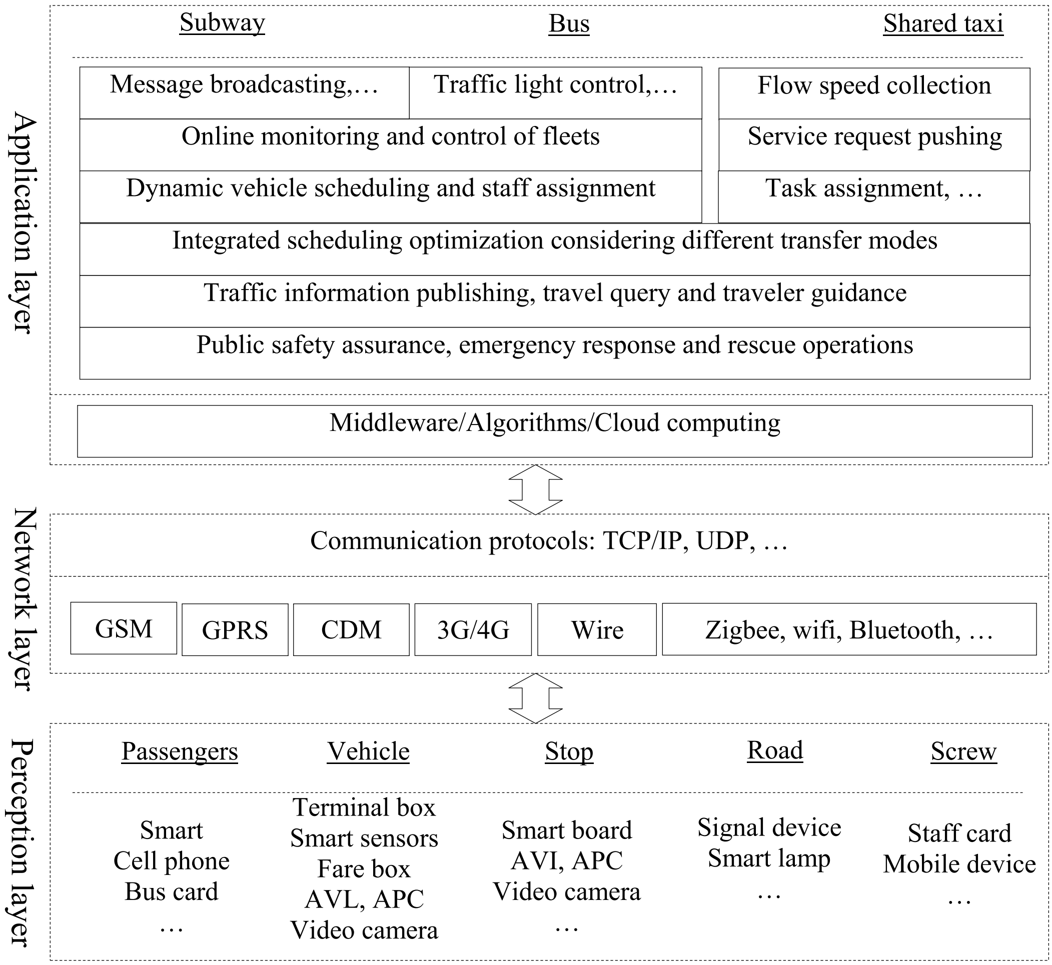

FIGURE 2. The three-tier architecture of the system based on IoT.

be further divided into public wireless communication and private wireless communication. Typical examples of public wireless communication include Global System for Mobile Communication (GSM), General Packet Radio Service (GPRS), Code Division Multiple Access (CDMA), the 3rd Generation communication (3G), and the 4th Generation communication (4G), etc. Public wireless communication can be used for transmission of vehicle status or traffic flow information with relatively long distance. Private wireless communications, on the other hand, usually include Zigbee, wifi and Bluetooth, etc., can be used connecting smart sensors to terminals installed on vehicles or bus stops.

(3) Application layer: it processes the data received from perception layer and provides applications for passengers or staff of the transportation system. It can be divided into platform sub-layer and business sub-layer. In platform sub-layer, the common methods and algorithms are encapsulated into middleware with the support of cloud computing. For example, data mining algorithms are deployed to find the regular characters of network traffic flow. In business sub-layer, various applications are available for different transportation fields. For shared taxi system, flow speed collection application can be installed on taxi to obtain the real time road network status; service request pushing application can be used to push passenger travel request to taxi drivers; task assignment application can be used to assign a transfer service of passenger to a driver with some optimization objectives. For subway system, some specific applications such as message broadcasting can be used based on the data. For bus system, traffic light control and green wave control can be applied to keep the strategy of public transport priority. For the road transportation systems, online monitoring and control of vehicles are used based on the real time locations of the vehicles and dynamic vehicle scheduling and staff assignment are used to maximize the utilization rate of transportation resources. Since passengers may transfer from different modes such as subway, bus and shared taxi, integrated scheduling can be applied to optimize the overall efficiency of the system. Based on the real time information of road network and pubic vehicles, application from the perspective of travelers such as traffic information publishing, travel query and traveler guidance are deployed for public convenience. Finally, public safety assurance, emergency response

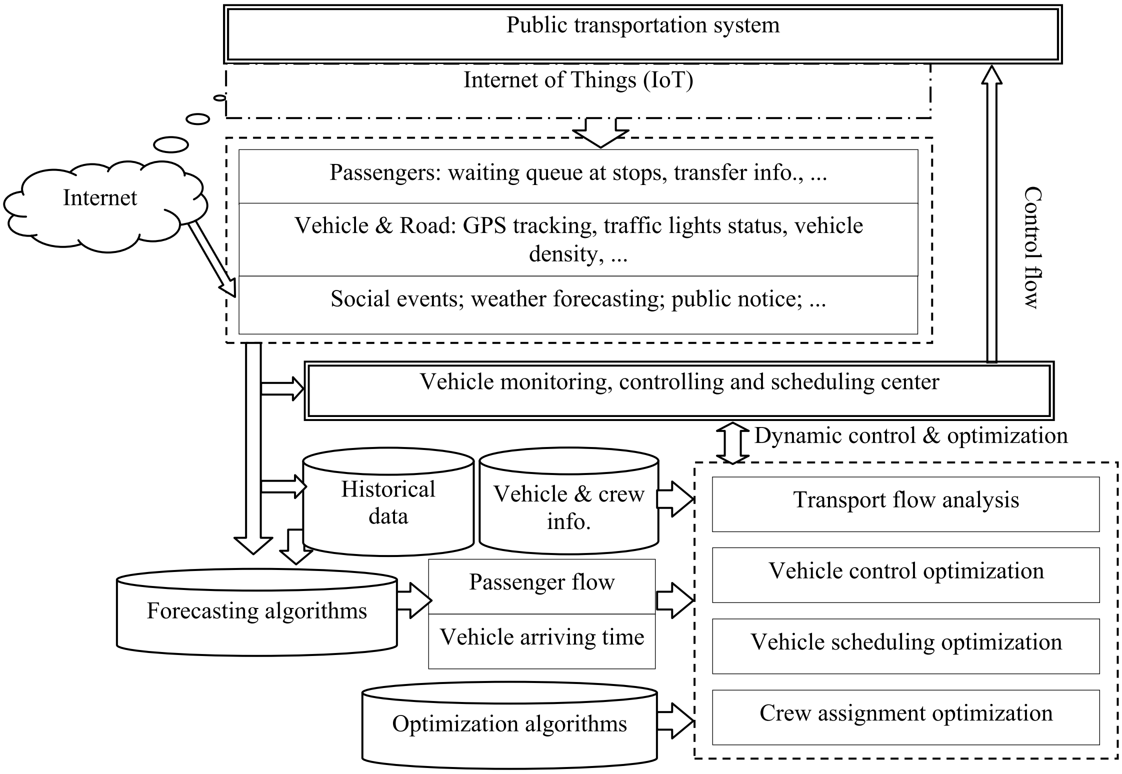

FIGURE 3. Information flow of the dynamic scheduling and controlling system.

and rescue operations, which are the indispensable parts of the public transportation system, are also deployed in this layer.

IV. DYNAMIC SCHEDULING AND CONTROLLING SYSTEM

In the proposed framework of the public transportation system based on IoT, the implementation of dynamic scheduling and controlling of vehicles is the kernel part. Since IoT makes it possible that multiple source of rich data can be obtained, the public transportation system can take full advantage of the IoT data and improve the efficiency of the system by dynamically scheduling and controlling the vehicles and assigning vehicle screw.

The information flow of the dynamic scheduling and control system is shown in Figure 3. The real time information of public transportation system collected by the IoT devices, including passenger's waiting queue at stops, vehicle GPS tracking, traffic lights status and vehicle density of roads, etc., is combined with the information extracted from internet such as social events, weather forecasting, public notice, traveling trends. Then the information is sent to the vehicle monitoring and controlling center as the input for storage and processing. The historical data of the transportation information are further analyzed to extract useful patterns or rules, e.g., morning peaks of passenger flows at particular stops. The passenger flow and vehicle arriving time are calculated by forecasting algorithms based on the generated patterns and real time information. The dynamic module for optimization and control is the core element of the system, which applies optimization algorithms to find the optimal solutions to vehicle dispatching based on the forecasted parameters and the current transit resources (e.g., the available vehicles and crew members). The vehicle controlling center collects the real time information in certain time intervals, adjusts the previous solution based on updated information, and information, and sends the control instructions to the public transportation system.

There are mainly four modules in the dynamic scheduling and control system, i.e., passenger flow analysis, vehicle control optimization, vehicle scheduling optimization, crew assignment optimization. The modules are introduced in detailed in the follows.

(1) Transport flow analysis: the data from IoT has the characteristics of mass volume from multiple sources, various forms including video and real time with variation. Transport flow includes road network flow and passenger flow. There are three steps for data analysis: a) data preprocessing, which eliminates the noises of IoT sensor by filtering algorithms and normalizes the data; b) pattern mining, which explores the useful patterns from historical transportation flow data and finds meaningful rules; c) flow prediction, which predicts the future road status and passenger ODs based on time series prediction algorithms and the explored patterns in the previous step. The technical scheme of the flow analysis is show in Figure 4.

(2) Dynamic vehicle control optimization: under the environment of IoT, the scheduling and controlling system can communicate with the drivers of running vehicles,

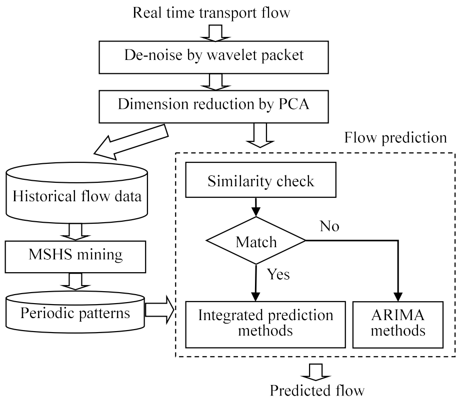

FIGURE 4. Technical scheme of the transport flow analysis.

send instructions to them, and monitor the control effect. For drivers of buses, the control strategies involve holding strategy, which is used at bus stops, and bus speed adjustment strategy, which is used between bus stops. For drivers of shared taxi, the control strategies can adjust the routings of shared taxis.

(3) Dynamic vehicle scheduling optimization: according to real time information collected by IoT, the scheduling and controlling system dynamically adjust the scheduling plans and determine the optimal vehicle dispatching time. When IoT of the transportation system detects irregular road network flow or passenger flow, the scheduling and controlling system can use special scheduling strategies which dispatch vehicles which do not stop at each bus station, e.g., short turning and deadheading.

(4) Dynamic crew assignment optimization: in case there is emergence case happened to vehicle screw, e.g., sick, unable to driver or temporary redeployment, the scheduling and controlling system re-assigns new screw member to the vehicle and minimize the impacts of the assignment adjustment.

The abovementioned modules of the dynamic scheduling and control system are developed based on optimization problem formulation under different scenarios and utilization of operation research theories. Based on mathematic modeling of scheduling optimization problem and the memory-based evolutionary computation algorithms, we have developed the intelligent public transport system for dynamic bus control and scheduling under the context of IoT. Some graphical user interfaces of our developed intelligent public transport system are shown in Figure 5.

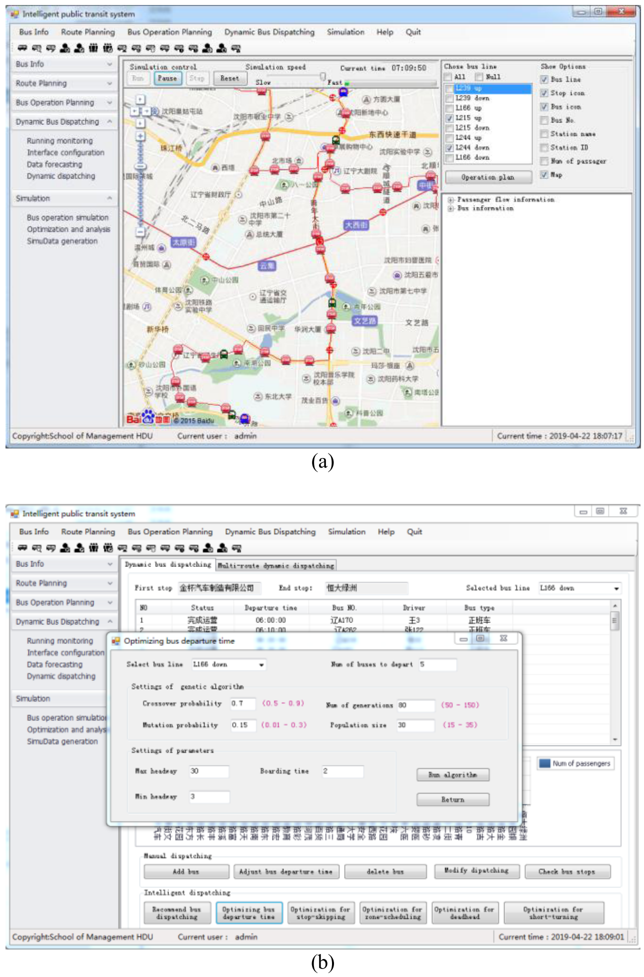

FIGURE 5. Some GUIs of the developed module for the intelligent public transport system. (a) Bus line visualization. (b) Optimization.

V. MATHEMATICAL MODEL AND SOLVING ALGORITHM

In this section, the mathematical model process of the dynamic bus scheduling optimization is given in detail. To solve the optimization model, a DSS-based evolutionary computation algorithm is developed.

A. OPTIMIZATION MODEL FOR DYNAMIC BUS SCHEDULING

Similar to the dynamic scheduling of plant processing [16], the method of rolling time windows is applied for the modeling of dynamic bus scheduling optimization. At a specified time point, some buses in a fleet have departed from the initial stop and some buses are still in the waiting queue. Based on the real-time information, the departure time of the buses in the waiting queue will be recalculated to obtain the optimal timetable and the speeds of running buses will be adjusted to obtain the optimal performance for the current period (time window); this time window is defined as a planning horizon. The planned optimization model is based on a specified planning horizon and can be used repeatedly for other planning horizons with different running parameters. As time passes, the planning horizon moves forward with a discrete time step.

Assumptions for the modeling include:

1) the buses in a fleet are homogeneous, i.e., the capacity and the number of seats is identical for each bus;
2) no accident occurs during the considered time period;
3) A bus driver can communicate with the control center via bus-mounted equipments and adjust the bus speed before the bus is departed from a stop.
4) The running speed of a bus between two adjacent stops is unchanged after the bus is departed from a stop.

5) the distribution curve of the passenger arrival rates for each stop can be estimated based on the data of the IoT environment and is unchanged during a planning horizon;
6) buses serve all stops; holding strategy and overtaking are not permitted;
7) Waiting time of a bus at a stop is estimated as the sum of the boarding time of passengers in the stop queue and the alighting time of the passengers on the bus.

The nomenclature related to the model is given as below:

NOMENCLATURE

T	length of a planning horizon
n^{B1}	number of buses running on the bus line
n^{B2}	number of buses that are going to depart at current planning horizon
n^S	number of stops of the bus line
$C^{\max}$	capacity of buses
D_m	distance between stop $(m-1)$ and stop m
T^{board}	boarding or alighting time for single passenger
$H^{\min}$, $H^{\max}$	minimal and maximal headway between adjacent buses, respectively
$V^{\min}$, $V^{\max}$	minimal and maximal average bus running speed, respectively
D_i^{now}	distance between bus i and the last visited stop; particularly, $D_i^{now} = 0$ if a bus does not depart
τ_i^U	index of the last visited stop by bus i; particularly, $\tau_i^U = 0$ for buses that are going to depart
$N_i^{now\_on}$	numbers of passengers on bus i at the start time of a planning horizon
$N_m^{now\_wait}$	numbers of passengers waiting at stop m at the start time of a planning horizon
$f_m(t)$	passenger arrival rate function at stop m
β_m	proportion of passengers who alight at stop m
X_{im}	departure time of bus i from stop m $(m \geq 1)$, and $X_{i0} = 0$ particularly
t_{im}^{arrive}	arrival time of bus i at stop m
γ_m	weighting factor affecting the average running speed of the bus i between the stop $m-1$and the stop m
N_{im}^{wait}	numbers of passengers who are waiting for bus $i$at stop m
N_{im}^{board}	numbers of passengers who board bus i at stop m
N_{im}^{left}	numbers of passengers who are left behind by bus $i$at stop m
N_{im}^{alight}	numbers of passengers who alight bus i at stop m
N_{im}^{on}	number of passengers on bus i when it arrives at stop m
T^{avg_w}	average waiting time of a passenger left behind by the last bus
T^{trip}	upper limit of time for a bus trip of the bus line

Decision variables of the optimization problem include:

X_{i1}	departure time at the initial stop for bus i in the planning horizon; Note that the last subscript of X is 1, which indicates that the decision variable only controls the departure time at the first stop and no holding strategy is considered.
V_{im}	average running speed of the bus i between the stop $m-1$ and the stop m.

The main purpose of the dynamic bus scheduling is to improve the service level of the transit system, which is reflected by evaluation criteria such as waiting time, accessibility, travel time, reliability, directness of service, frequency of service, passenger density, etc. [17]. Among these criteria of level of service, passenger wait time is the most widely used objective in the literature related to bus scheduling and control [18], [19]. Therefore, minimizing the total waiting time of passengers is taken as the objective of the optimization model in this research.

The total waiting time of passengers can be divided into the following two parts.

(1) Time spent by the passengers waiting for the first arrival of bus i at stop m in the current planning horizon:

$$T^{first} = \sum_{i=1}^{n^{B1}+n^{B2}} \sum_{m=1}^{n^S} \int_{X_{(i-1)m}}^{X_{im}} (X_{im} - t) f_m(t)\, dt \tag{1}$$

(2) Time spent by the passengers who did not get on the previous bus due to bus capacity limit and are waiting for the arrival of bus i at stop m:

$$T^{left} = \sum_{i=1}^{n^{B1}+n^{B2}} \sum_{m=1}^{n^S} N_{im}^{left} [X_{im} - X_{(i-1)m}] + \sum_{m=1}^{n^S} T^{avg\_w N^{left}_{(n_P^{B1}+n_P^{B2})m}} \tag{2}$$

where the first part of the equation is the time spent by the passengers who are left and wait for the arrival of bus i at stop m and the second part is the extra waiting time of passengers who are left behind by the last bus in the planning horizon.

The objective of the optimization model is to minimize the sum of the abovementioned two parts, i.e.,

$$\text{Min } Z = T^{first} + T^{left} \tag{3}$$

When a bus running on a line at the beginning of the planning horizon reaches the next stop, the number of passengers on this bus can be directly initialized, i.e.,

$$N_{im}^{on} = N_i^{now\_on} \quad i = 1, 2, \ldots, n^{B1}; \quad m = \tau_i^U + 1; \tag{4}$$

The number of passengers on this bus when it reaches one of the subsequent stops equals the number of passengers at the previous stop minus the number of passengers that alight at that stop plus the number of passengers that boarded the bus at the previous stop, which can be expressed as the following recursive formula:

$$\begin{aligned} N_{im}^{on} &= N_{i(m-1)}^{on} + N_{i(m-1)}^{board} - N_{i(m-1)}^{alight} \quad i = 1, 2, \ldots, n^{B1}; \\ & m = \tau_i^U + 2, \cdot\cdot, n^S \\ & \text{or } i = n^{B1} + 1, \ldots, n^{B1} + n^{B2}; \quad m = \tau_i^U + 1, \cdot\cdot, n^S \end{aligned} \tag{5}$$

The arrival time of a bus is calculated under two scenarios: 1) Scenario 1: a bus is already running on a line at the beginning of the planning horizon; the arrival time of the bus at the next stop is related to the distance between the current position and the next stop, hence the arrival time is formulated as:

$$\begin{aligned} t_{im}^{arrive} &= (D_{pm} - D_{pi}^{now})/(\gamma_m V_{im}) \quad i = 1, 2, \ldots, n^{B1}; \\ & m = \tau_i^U + 1; \end{aligned} \tag{6}$$

2) Scenario 2: in other cases, the arrival time of the bus at the next stop is related to the departure time of the upstream stop and the distance between the two adjacent stops, hence the bus arrival time is formulated as:

$$\begin{aligned} t_{im}^{arrive} &= X_{i(m-1)} + D_m/(\gamma_m V_{im}) \quad i = 1, 2, \ldots, n^{B1}; \\ & m = \tau_i^U + 2, \ldots, n^S; \\ & \text{or } i = n^{B1} + 1, \ldots, n^{B1} + n^{B2}; \quad m = \tau_i^U + 1, \ldots, n^S; \end{aligned} \tag{7}$$

According to the assumption, the number of passengers who will alight a bus at a stop is a proportion of the number of total passengers on the bus, i.e.,

$$\begin{aligned} N_{im}^{alight} &= \beta_m N_{im}^{on} \quad i = 1, 2, \ldots, n^{B1} + n^{B2}; \\ & m = \tau_i^U + 1, \ldots, n^S - 1; \end{aligned} \tag{8}$$

For the buses running on a line at the beginning of the planning horizon, the numbers of passengers who are waiting for a bus at a stop is formulated as:

$$\begin{aligned} N_{im}^{wait} &= N_m^{now_wait} + \int_0^{t_{im}^{arrive}} f_m(t)\, dt \quad i = 1, 2, \ldots, n^{B1}; \\ & m = 1, 2, \ldots, n^S - 1; \end{aligned} \tag{9}$$

where the first element of the right part of the equation is the number of passengers who are already in the waiting queue at the beginning of the planning horizon; the second part is the number of passengers who arrive during a period from the beginning of the planning horizon to the arrival of the bus i.

If the remaining bus capacity is larger than the number of passengers who want to board the bus, then all passengers can get on the bus; otherwise, only a limited number of passengers can get on the bus. Therefore, the number of passengers who are able to board a bus can be formulated as:

$$\begin{aligned} N_{im}^{board} &= \min\{C^{\max} - N_{im}^{on} + N_{im}^{alight}, N_{im}^{wait}\} \\ & i = 1, 2, \ldots, n^{B1} + n^{B2}; \quad m = 1, 2, \ldots, n^S - 1; \end{aligned} \tag{10}$$

The number of passengers who are unable to board the bus at a stop equals the total numbers of passengers who have been waiting there minus the passengers who are able to board the bus, i.e.,

$$\begin{aligned} N_{im}^{left} &= N_{im}^{wait} - N_{im}^{board} \\ & i = 1, 2, \ldots, n^{B1} + n^{B2}; \quad m = 1, 2, \cdot\cdot, n^S - 1; \end{aligned} \tag{11}$$

For the buses that did not depart at the beginning of the planning horizon, the number of passengers who are waiting for a bus at a stop is formulated as:

$$\begin{aligned} N_{im}^{wait} &= N_{(i-1)m}^{left} + \int_{t_{(i-1)m}^{arrive}}^{t_{im}^{arrive}} f_m(t)\, dt \\ & i = n^{B1} + 1, \ldots, n^{B1} + n^{B2}; \quad m = 1, 2, \ldots, n^S - 1; \end{aligned} \tag{12}$$

where the first element of the right part of the equation is the number of passengers who cannot take the previous bus due to a capacity limit, and the second part is the number of passengers who arrive from the time of arrival of bus (i-1) to the time of arrival of bus i.

The departure time of a bus at a stop is determined by its arrival time and the time spent alighting or boarding, i.e.,

$$\begin{aligned} X_{im} &= t_{im}^{arrive} + T^{board} \max\{N_{im}^{board}, \beta_m N_{im}^{on}\} \\ & i = 1, 2, \ldots, n^{B1} + n^{B2}; \quad m = \tau_i^U + 1, \ldots, n^S - 1; \end{aligned} \tag{13}$$

The average waiting time spent by the passengers who are left behind by the last bus at a planning horizon can be estimated by equation (14).

$$T^{avg\_w} = \sum_{m=1}^{n^S-1} (X_{(n^{B1}+n^{B2})m} - X_{(n^{B1}+n^{B2}-1)m})/(n^S - 1) \tag{14}$$

The optimization model of the bus scheduling in a planning horizon is formulated as follows.

$$\begin{aligned} \min_{X_{i1}, V_{im}} Z = & \sum_{i=2}^{n^{B1}+n^{B2}} \sum_{m=1}^{n^S} \int_{X_{(i-1)m}}^{X_{im}} (X_{im} - t) f_m(t)\, dt \\ & + \sum_{i=2}^{n^{B1}+n^{B2}} \sum_{m=1}^{n^S} N_{im}^{left} [X_{im} - X_{(i-1)m}] \\ & + \sum_{m=1}^{n^S} T^{avg_w} N_{(n^{B1}+n^{B2})m}^{left} \end{aligned} \tag{15}$$

$$\begin{aligned} \text{s.t. } H^{\min} \le X_{im} - X_{(i-1)m} \le H^{\max} \quad & i = 2, \ldots, n^{B1}; \\ & m = \tau_i^U + 2, \cdot\cdot, n^S; \\ \text{or } i = n^{B1} + 2, \ldots, n^{B1} + n^{B2}; \quad & m = \tau_i^U + 1, \ldots, n^S; \end{aligned} \tag{16}$$

$$X_{(n^{B1}+n^{B2})1} = T \tag{17}$$

$$V^{\min} \le V_{im} \le V^{\max} \quad i = 1, \ldots, n^{B1} + n^{B2}; \quad m = 1, 2, \ldots, n^S - 1; \tag{18}$$

$$t_{in^S}^{arrive} - X_{i1} \le T^{trip} \quad i = 1, \ldots, n^{B1} + n^{B2}; \tag{19}$$

X_{i1}, V_{im} are positive integers.

Equation (15) represents the objective function of the optimization model, i.e., minimizing the overall waiting time of passengers in the current planning horizon. Constraint (16) guarantees that the headway between two adjacent buses at all stops is within a given range and overtaking is not permitted in a line. Constraint (17) follows the assumption that the last bus departs at the end of the planning horizon. Constraint (18) confines the range of the bus speeds (decisions variables). Constraint (19) ensures that the trip time of every bus from the initial stop to the end stop does not exceed the upper limit.

B. DSS-BASED EVOLUTIONARY COMPUTATION ALGORITHM

Since the optimization models of dynamic scheduling problems from the perspective of real time operations level are non-linear and very complex, meta-heuristic algorithms are applied to solve these models. Figure 6 shows the proposed evolutionary computation algorithms based on the decision support system (DSS) for multiple planning horizons.

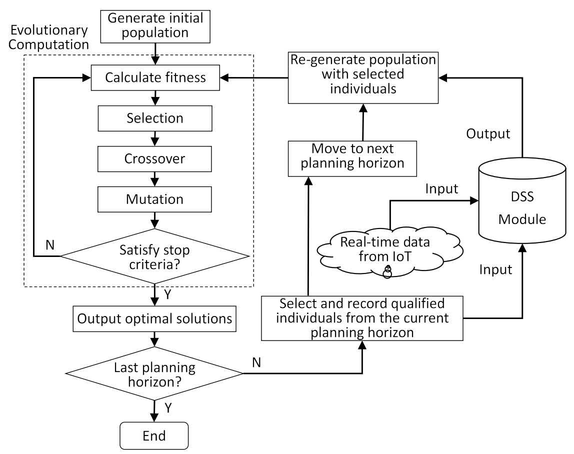

FIGURE 6. Main flow of the DSS-based evolutionary computation algorithm.

The basic idea of the DSS-based initialization is that, the information of the high-quality solutions of the last generation of the algorithm is stored in the memory and to be prepared for the initialization of the next population. As shown in figure, the population of the first planning horizon is generated in random. After the iteration process of the algorithm is finished, some high-quality solutions are elicited from the last generation of the current planning horizon and recorded in memory. Then, the time window is moved to the next planning horizon, and the real-time information of the IoT, such as positions of running vehicles and number of waiting passengers at each stop, is imported into the system and the model parameters are updated accordingly. The population of the algorithm under the new environment includes two parts: the first part is generated in random; another part is generated by incorporating information extracted from the best-quality solutions stored in memory. The outer loop of the algorithm stops until the last planning horizon is reached.

Some detailed descriptions of the evolutionary computation algorithm are given as follow.

1) CODING STRUCTURE

To facilitate the genetic operators, the chromosome is designed based on the headway instead of bus departure time. The encoding of an individual is expressed as $[H^1, H^2, \ldots, H^{n^{B2}}; V_{11}, V_{12}, \ldots, V_{1(n^S-1)}, V_{21}, V_{22}, \ldots, V_{2(n^S-1)}, \ldots, V_{(n^{B1}+n^{B2})(n^S-1)};]$ in which there are two sections, i.e., headway section and bus speed section. In headway section, there are n^{B^2} genes, and a gene stands for the headway between two adjacent buses, e.g., H^2 represents the headway between the first bus and second bus. Particularly, H^1 represents the headway between the start time of the current planning horizon and the first bus. In bus speed section, there are $(n^{B1} + n^{B2})(n^S - 1)$ genes, and each gene represents the average bus running speed for a particular bus between two adjacent bus stops, e.g., V_{21} represents the average bus running speed of bus 2 between the first stop and second stop.

2) FITNESS FUNCTION

As shown by equation (15), the objective function of the model is the total waiting time of passengers. The fitness function of an individual is defined as

$$f = (Z^{\max} - Z)/(Z^{\max} - Z^{\min}) \tag{20}$$

where Z is value of the objective function of the individual, $Z^{\max}$ and $Z^{\min}$ are the largest and smallest values of the objective functions in the current generation.

3) CROSSOVER

Uniform crossover [20] are adopted for the crossover operation of the individuals. First, a 0-1 crossover mask with the same structure as the chromosome is randomly generated, then the genes of the two parents which correspond the '1' element of crossover mask is swapped to form the two child individuals. However, the children individuals after crossover may be invalid. For example, the sum of the headways represented by genes in the headway section of the chromosome does not equal to the length of a planning horizon, or the trip time corresponding to the bus speed section of the chromosome is larger than the upper limit. In this case, the children individuals also need to be repaired.

4) MUTATION

Neighborhood moving mutation is applied for generating new individuals. The operation process is as follows: randomly select several pairs of genes in the headway section of an individual, then add one to the value of one gene, and decrease one to the value of another gene; randomly select some

TABLE 1. Passenger arrival rate - uniform-type flow.

Density	Time								
	10:00	10:20	10:40	11:00	11:20	11:40	12:00	12:20	12:40
High	1.1	1.08	1.1	1.09	1.2	1.18	1.16	1.13	1.1
Mid	0.8	0.75	0.77	0.79	0.82	0.79	0.83	0.8	0.78
Low	0.4	0.45	0.43	0.48	0.5	0.51	0.43	0.47	0.45

*Note: unit of passenger arrival rate is person/minute

genes in the bus speed section of the individual, then add one or decrease one at random to the value of the genes. The purpose of adopting the gene pairs in the headway section is to ensure that the sum of the headways equals to the planning horizon T.

5) CHROMOSOME-REPAIRING MECHANISM

After crossover or mutation operation, the generated chromosome may violate the constraints of the optimization model. The simplest way to tackle this situation is to abandon this chromosome and re-generate a new one, but this may deteriorate the performance of the evolutionary process. Therefore, a normalization-based repairing procedure for the invalid chromosome is applied. For example, if an individual after crossover does not satisfy the sum-of-headways constraint although the value of any gene is within the range of headway, the vector of the headway section can be re-adjusted according to Equation (21).

$$\langle H^1, H^2, \ldots, H^{n^{B2}} \rangle = \left\lceil \langle H^1, H^2, \ldots, H^{n^{B2}} \rangle \cdot T / \sum_{i=1}^{n^{B2}} H^i \right\rceil \tag{21}$$

where the ceiling mark represents that the calculated parameters are rounded to integer and the sum of the headways is T. By following this strategy, the mode or shape of the series of headways can be basically maintained and headway constraint is also satisfied.

VI. EVALUATION AND EXPERIMENTAL RESULTS

To evaluate the proposed dynamic scheduling model and solving algorithms, a case study with real public transit bus line data is performed. The bus line is part of the public transit network in Shenyang city, capital of Liaoning province of the P.R.C. The real-time passenger flow information and the real-time bus running speed information over seven days were provided by the public transit company operating the bus line. The bus line has 24 stops and the length of line is 16.8 km. The average distance of two adjacent stops is 0.7 km. The capacity of the buses of the line is 40 passengers. The average running speed of the bus with considering the traffic light waiting time is between 5km to 15km. The average boarding and alighting time for single passenger is about 5s.

The algorithm is programmed in a C# 2010 environment. The experiments were run on a laptop computer (Intel(R) Core(TM) 2 i7-4500U @ 1.80 GHz; 8G RAM; Microsoft Windows 7).

A. EXPERIMENTS FOR SINGLE PLANNING HORIZON

The interval of the departure time determined by the transit agency is 10 minutes for all buses, which is commonly used in many transit systems. The bus fleet in a planning horizon includes 8 buses and thus seven headways and bus running speeds at stops need to be optimized. Genetic algorithm is developed to solve the optimization model for single planning horizon. The relevant control parameters of the genetic algorithm are set as follows: the population size is 70; the number of iteration is 500; the crossover rate is 0.8; the mutation rate is 0.3. By carefully analyzing the passenger flow of the public transit, it can be observed that the passenger flow has some regular patterns although the situations in different time segments are different in one day. Four main types of passenger flows are summarized and numeric experiments are performed based on different types of passenger flows and the optimal bus scheduling solutions are obtained and compared.

(1) Uniform-type flow. This type usually appears in daytime between morning peak hours and evening peak hours. The average passenger arrival rates of stops are almost the same or little fluctuation with the change of time. The planning horizon is between 10am and 12am, and the passenger arrival rates are considered with three types of densities, i.e., high, middle and low. The detailed passenger arrival rates (person/minute) are given in Table 1.

The experimental results under three types of passenger flows are given in Table 2. The initial solution, which adopts the fixed frequency to depart the buses and the bus running speed keeps unchanged, is the default scheme used by the transit agency. The second solution and the third solution are obtained by taking bus dispatching time as decision variables and by taking bus dispatching time & bus running speeds as decision variables, respectively. It is observed that, the overall passenger waiting times of three solutions are different. However, T^{left} of them are 0, indicating that there are no passengers who did not get on the previous bus due to bus capacity limit. By observing the value of T^{first}, it can be found that the initial solution has the worst performance. If the bus dispatching times or headways are taken as decision variables, the performance of the obtained solution is improved but the optimization rate is below 5% and the optimization effect is not obvious. However, if both headways and bus running

TABLE 2. Three optimization results and comparisons - uniform-type flow.

F.D.	Solutions	Headway							Objective		Opt. rate
		1	2	3	4	5	6	7	T^{first}	T^{left}	
High	I	10	10	10	10	10	10	10	10732.4	0	-
	D	11	10	11	11	11	9	7	10227.1	0	4.7%
	D&S	12	11	10	9	10	10	8	9110.3	0	15.1%
Mid	I	10	10	10	10	10	10	10	7828.7	0	-
	D	11	11	9	11	12	9	7	7567.0	0	3.3%
	D&S	11	11	11	10	8	11	8	6422.5	0	17.9%
Low	I	10	10	10	10	10	10	10	4172.3	0	-
	D	11	11	10	10	10	10	8	4155.2	0	0.4%
	D&S	10	12	11	8	11	10	8	3320.2	0	20.4%

*Note: I-initial solution; D-bus dispatching time as variables; D&S- bus dispatching time and bus speed as variables; Unit of headway or objective function value is minute.

TABLE 3. Passenger arrival rate - inclining-type flow.

Density	Time									
	7:00	7:15	7:30	7:45	8:00	8:15	8.30	8:45	9:00	9:15
High	1.10	1.17	1.23	1.30	1.36	1.43	1.46	1.50	1.56	1.63
Mid	0.73	0.74	0.80	0.88	0.97	1.07	1.09	1.10	1.14	1.17
Low	0.48	0.54	0.55	0.60	0.68	0.75	0.78	0.80	0.82	0.90

TABLE 4. Three optimization results and comparisons - inclining-type flow.

F.D.	Solutions	Headway							Objective		Opt. rate
		1	2	3	4	5	6	7	T^{first}	T^{left}	
High	I	10	10	10	10	10	10	10	13101.73	3260.9	-
	D	11	11	12	10	9	9	8	12200.42	2355.7	11.0%
	D&S	11	10	11	9	12	9	8	11664.14	1485.7	19.6%
Mid	I	10	10	10	10	10	10	10	9262.14	0	-
	D	10	12	12	11	8	9	8	9052.00	0	2.2%
	D&S	12	11	9	9	10	9	10	7172.99	0	22.5%
Low	I	10	10	10	10	10	10	10	7192.61	0	-
	D	11	10	11	11	9	10	8	6843.73	0	4.6%
	D&S	10	11	9	10	12	8	10	5391.87	0	25.0%

speed are taken as decision variables, the performance can be improved over 15% for all three flow density conditions, indicating that this scheduling strategy is suitable for the scenario with uniform-type flow. Since there are 8 buses and 24 stops (23 speed variables for each bus), the optimal bus running speeds of the bus at the segments of the trip are not listed in the table due to limited space.

(2) Inclining-type flow. This usually happens at the beginning of the morning peak hour or the evening peak hour. The average passenger arrival rates of stops increase with the time. The planning horizon is between 7am and 9:15 am, and the passenger arrival rates are considered with three types of densities, i.e., high, middle and low. The detailed passenger arrival rates are given in Table 3.

The experimental results for inclining-type flow under three types of densities are given in Table 4. If the departure times of buses are taken as decision variables and bus speeds are fixed, the resulted optimal headways are firstly longer and then shorter. This result corresponds to the distribution characteristics of the inclining type flow, i.e., the frequency of bus dispatching should be higher for the larger passenger arrive rate at the latter part of the flow. By observing Table 4, it can be found that T^{left} of the initial solution is quite large because many passengers cannot get on the bus due to bus capacity limit. If both departure times and bus speeds are adjustable, not only T^{left} is saved, T^{first} can also be improved substantially. The optimization rates compared with the initial solution for all three flow density conditions are 19.6%, 22.5 and 25%, respectively. This indicates that the strategy of dynamic scheduling and dynamic adjusting bus speed has good performance.

(3) Declining-type flow. This type of flow usually appears at the end of the morning peak hour or the evening peak hour. The average passenger arrival rates of stops decrease with the time. The planning horizon is between 18:30am and 20:45 am, and the passenger arrival rates are also considered with three types of densities. The detailed passenger arrival rates are given in Table 5.

TABLE 5. Passenger arrival rate - declining-type flow.

Density	Time									
	18:30	18:45	19:00	19:15	19:30	19:45	20:00	20:15	20:30	20:45
High	1.10	1.08	1.05	1.00	0.99	0.96	0.90	0.87	0.86	0.80
Mid	0.80	0.75	0.73	0.71	0.68	0.65	0.58	0.55	0.44	0.45
Low	0.52	0.50	0.50	0.45	0.42	0.30	0.33	0.28	0.30	0.30

TABLE 6. Three optimization results and comparisons - declining-type flow.

F.D.	Solutions	Headway							Objective		Opt. rate
		1	2	3	4	5	6	7	T^{first}	T^{left}	
High	I	10	10	10	10	10	10	10	8340.9	169.1	-
	D	10	8	10	10	11	12	9	8075.4	227.3	2.4%
	D&S	9	11	9	9	10	11	11	6629.1	0	22.2%
Mid	I	10	10	10	10	10	10	10	5333.7	0	-
	D	9	9	10	10	10	11	11	4917.8	0	7.7%
	D&S	12	11	10	9	8	9	11	4072.5	0	23.6%
Low	I	10	10	10	10	10	10	10	3625.1	0	-
	D	10	10	10	10	11	11	8	3493.6	0	3.6%
	D&S	13	10	7	13	10	8	9	2692.9	0	25.7%

TABLE 7. Passenger arrival rate - convex-type flow.

Density	Time									
	7:00	7:20	7:40	8:00	8:20	8:40	9:00	9:20	9:40	10:00
High	0.75	0.82	0.85	0.94	0.98	1.10	1.02	0.94	0.87	0.86
Mid	0.52	0.60	0.63	0.65	0.77	0.72	0.72	0.68	0.66	0.63
Low	0.38	0.40	0.43	0.45	0.50	0.55	0.48	0.42	0.40	0.40

TABLE 8. Three optimization results and comparisons - convex-type flow.

F.D.	Solutions	Headway							Objective		Opt. rate
		1	2	3	4	5	6	7	T^{first}	T^{left}	
High	I	10	10	10	10	10	10	10	9457.7	142.9	-
	D	10	11	11	10	10	10	8	9210.6	259.1	2.4%
	D&S	11	10	10	10	9	9	11	8170.1	0	14.2%
Mid	I	10	10	10	10	10	10	10	6590.5	0	-
	D	10	11	11	11	10	9	8	6417.4	0	2.6%
	D&S	12	11	10	9	8	9	11	51617	0	21.7%
Low	I	10	10	10	10	10	10	10	4471.7	0	-
	D	10	11	11	10	11	7	10	4302.6	0	3.6%
	D&S	11	12	9	8	11	9	10	3315.3	0	25.8%

The experimental results for declining-type flow under three types of passenger densities are given in Table 6. Under the high density flow, since the passenger arrive rates are large for the front half part of the time, some passengers cannot get on the bus due to bus capacity limit (T^{left} is not equal to 0) if the initial solution is adopted. If the bus dispatching times are adjusted, the overall passenger waiting time and T^{first} are both deceased although T^{first} is slightly creased from 169.1 to 227.3. However, if the bus dispatching times and bus running speed are dynamically adjusted, T^{left} under the three kinds of densities are 0 and T^{first} are also decreased substantially, and the performance can be improved over 20% compared with the initial solution for all three flow density conditions.

(4) Convex-type flow. This usually appears when some public events, e.g., celebrations, are hold, resulting that the average passenger arrival rates of stops first increase that then decrease gradually. The planning horizon is between 7am and 10 am and the detailed passenger arrival rates are given in Table 7.

The experimental results under three types of flow densities are given in Table 8. It can be observed from the table that, if the bus dispatching times are taken as decision variables, the optimization rates of the obtained solutions under the high, mid, and low passenger flow densities are 2.4%, 2.6%, and 3.6%, respectively. However, if bus running speeds are also taken as decision variables, the optimization rates of the

TABLE 9. Passenger arrival rates of multiple updating time points.

Time	Bus stop																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	1	1	1	1	1	1	1	1	2	2	3	3	2	2	2	2	1	1	1	1	1	1	1
1*Δt	1	1	1	1	1	1	2	2	2	3	4	4	3	3	2	2	2	2	2	1	1	1	1
2*Δt	1	1	1	1	1	1	2	3	3	4	5	4	4	3	3	2	2	2	2	1	1	1	1

TABLE 10. Road congestion indices for multiple updating time points.

Time	Bus stop																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	1	1	1	1	1	1	1	1	2	2	3	3	2	2	2	2	1	1	1	1	1	1	1
1*Δt	1	1	1	1	1	1	2	2	2	3	4	4	3	3	2	2	2	2	2	1	1	1	1
2*Δt	1	1	1	1	1	1	2	3	3	4	5	4	4	3	3	2	2	2	2	1	1	1	1

TABLE 11. Optimization results of the three planning horizons.

Time	Headway							Objective value		
	1	2	3	4	5	6	7	0 solution	1*Δt solution	2*Δt solution
0	8	10	11	11	9	9	12	1987.2	N/A	N/A
1*Δt	10	9	10	11	9	9	12	2633.2	2127.6	N/A
2*Δt	10	9	10	11	8	10	12	2354.2	2048.1	1820.3

obtained solutions under the three passenger flow densities are 14.2%, 21.7%, and 25.8%, respectively. This shows that D&S strategy can improve the performance of the bus line and is also suitable for the convex-type passenger flow.

It can be observed from the numeric experiments that, by applying the strategy of adjusting bus dispatching time and bus running speed, the overall passenger waiting time is reduced under different types of passenger flow and different densities of arrive rates. While the improvement of performance by adjusting bus dispatching time is effective but is not very obvious (optimization rate is 4% on average), adjusting bus dispatching time and bus running time can significantly improve the performance (optimization rate is 21.1% on average).

B. EXPERIMENTS FOR MULTIPLE PLANNING HORIZONS

In practical scenarios, the passenger flow distributions at stops and road congestion status of bus line are changing with time. When the real-time information related to the transit system is obtained by various equipments under the environment of IoT, the transit agency can dynamically schedule the buses to achieve the better performance. If multiple planning horizons are considered and the parameters of each planning horizon are obtained by the collected real-time information, the DSS-based genetic algorithm can be applied to rapidly find the near optimal solution for each planning horizon. In the following experiments, the time interval of information updating for bus line, Δt, was 5 minutes, i.e., the up-to-date passenger flow at stops and traffic congestion status were collected every 5 minutes. The time range for the planning horizons is between 7am to 10am, and the information was collected at the starting time point, at $1 * \Delta t$, and at $2 * \Delta t$, respectively. The average passenger arrival rates for the three time points are given in Table 9.

The road congestion statuses along the bus line are different with stops and also are changing with time. Table 10 shows the road congestion indices of the 23 road segments for the three updating time points, where the indices '1', '2', '3', '4' and '5' represent that the road status are 'clear', 'moderately clear', 'slightly jammed', 'moderately jammed' and 'heavily jammed', respectively. The road congestion indices are transformed into weighting factors which affect the bus running speeds. The number of buses in the fleet is also 8, and 23 bus running speeds need to be optimized. The detailed parameters of the DSS-based evolutionary computation algorithm are set as follows: the population size is 60; the number of iteration is 500; the crossover rate is 0.8; the mutation rate is 0.2.

Table 11 shows the experimental results for three planning horizons. The first row shows that the optimal headways at the starting planning point and the minimal passenger waiting time is 1987.2 minutes. The second rows shows that the optimal headways of the $1 * \Delta t$ time point is changed into "10 9 10 11 9 9 12" minutes, and the minimal passenger waiting time is 2127.6 minutes with the latest information of the $1 * \Delta t$ time point. However, if the dynamic scheduling strategy is not applied and the optimal solution at the starting planning point is used, the overall passenger waiting time is 2633.2 minutes and thus the improvement rate is 19.2%.

TABLE 12. Average bus running speed of the first bus in the fleet.

Time	Bus stop																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	8	12	12	10	11	9	11	11	11	9	11	8	11	11	11	11	9	12	10	12	7	7	7
$1*\Delta t$	8	12	12	10	12	12	11	10	9	8	10	8	10	11	10	11	9	12	10	12	7	7	7
$2*\Delta t$	8	12	12	7	7	8	9	10	6	7	5	6	7	6	8	7	11	12	8	8	8	9	7

Similarly, in the third row, minimal passenger waiting time is 1820.3 minutes with the information of the $2 * \Delta t$ time point. If the optimal solutions at the $1 * \Delta t$ time point and the starting planning point are used, the overall passenger waiting times are 2048.1 minutes and 2354.2 minutes, respectively; and thus the improvement rates are 11.1% and 22.7%, respectively. Table 12 shows the optimal average bus running speed (km/h) corresponding to the optimal solutions of the three planning horizons and speed data is only for the first bus in the fleet due to limited space.

By observing and analyzing the experimental results, it can be concluded that the proposed dynamic scheduling strategy based on multiple planning horizons can effectively utilize the real-time information of IoT environment and thus can achieve better performance for the transit system.

VII. CONCLUSIONS

As a promising paradigm of information technology, IoT attracts more and more attentions from various industrial fields. It can be estimated that the IoT technology will be deeply applied in the public transportation system and help the system provide more efficient public services in the near future. In this paper, the impact of IoT environment on the public transportation system are discussed, and a new framework of the intelligent public transportation system based on IoT is proposed. The deployment of the elements, the communication network and the three-tier architecture of the system are described in detail. The modules of the dynamic vehicle scheduling and controlling system, which is the kernel part of the whole public transportation system, are presented and analyzed. The information flow, technical scheme, mathematical model and optimization algorithms of the main modules of dynamic optimization are presented. The results of the numeric experiments show that the proposed dynamic scheduling strategy can effectively utilize the real-time information of IoT environment and improve the performance of the transit system. The proposed intelligent transport system based on IoT can assist the decision makers to increase the utilization rate of the transport resources, improve the efficiency of scheduling and reduce passengers' traveling time.

One of the limitations of our research is that large size complex real time data sets of bus lines are not available in the experiments of the case study, and this leaves room for further research on evaluate and improve the proposed optimization algorithm. Another research potential is to consider more factors related to uncertainty and disturbance in the transit system and apply robust optimization methods to model the problems and develop efficient algorithms.

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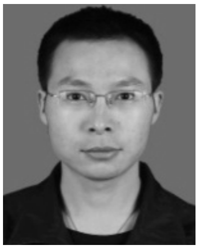

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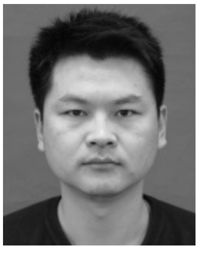

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