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修　士　論　文

顧客のパンクチュアリティ予測を備えた MaaS 共有バスシステムの設計

MaaS Shared Bus System Design with Customer Punctuality Prediction

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Abstract

Nowadays, Mobility as a Service (MaaS) as a novel idea of urban mobility framework has been widely developed and provides convenience for multiple transportation ways. However, though among all sorts of transportation, subway takes on the most travel pressure, and commuters still face with difficulties concerning methods to efficiently move between homes and subway stations with less transportation pollution.

To address these challenges, in this paper, we propose a novel MaaS shared bus sub-system framework, which can optimize an integrated subway station nearby shuttle bus route based on passengers’ travel demands, meanwhile adequately taking the punctuality of the passengers into account. Considering different business scenarios, the route planning is solved by proposed methods based on ant colony optimization. A real case experiment is applied to test the efficiency of the shared bus system, which can be served as a benchmark. Through the real case, the ability of the system to reduce environmental pollution is also demonstrated.

Keywords: Big Data, Bus Sharing, MaaS, Vehicle Routing Problem

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第 1 章

Introduction

1.1 Background

Nowadays, Mobility as a Service (MaaS), a new idea of urban mobility framework, has been extensively discussed and studied, which provides convenience for users through fast response to instant travel requests and efficient transportation planning [1][2]. MaaS enables users to plan, book, and pay for multiple types of mobility services through an joint digital channel. MaaS system performs well in mega cities with multiple transportation ways [3]. Among all sorts of transportation, subway takes on the most travel pressure [4]. Although subway system provides enormous convenience, commuters still face with difficulties about how to efficiently move between subway stations and destinations.[5]. Unfortunately, transportation policy makers and private-sector transportation service providers seldom pay attention to these issues, which indicates that there are still lots of chances to further decrease traffic pollution and save public transportation resource[6][7].

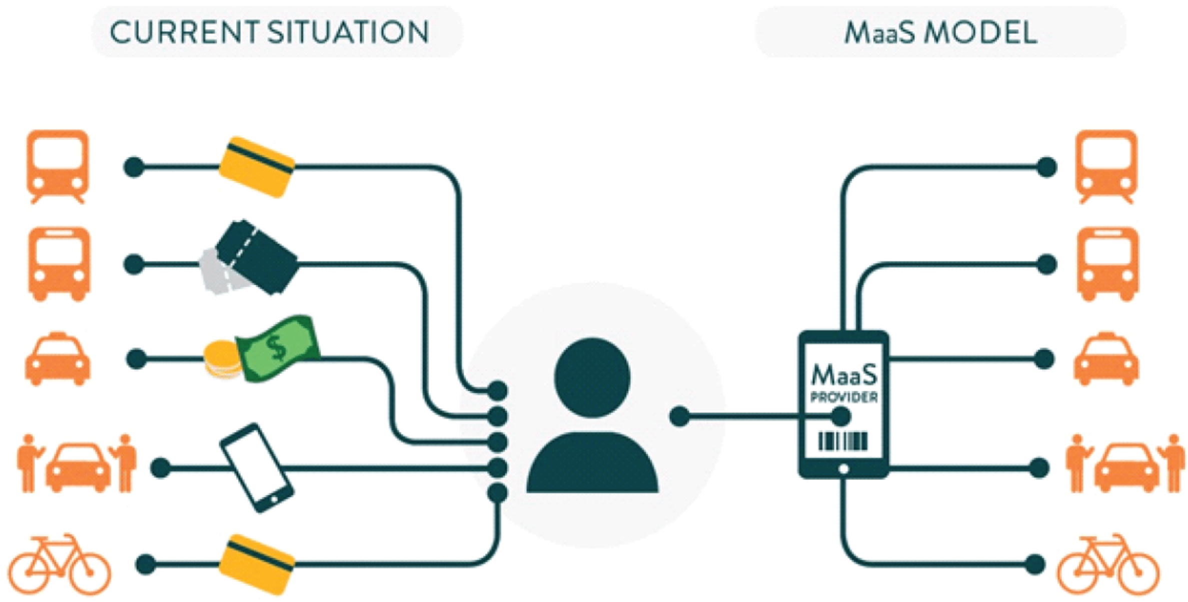


Fig.1.1: MaaS system concept.

As shown in Fig. 1.1[8], the traditional booking of tickets are various. From cash transactions, prepaid transportation cards to online payment, the complicated methods bring trouble and confusion to both local customers and tourists. The multiple ways of fee payment also restrict the possibility of integrate all the transportation methods. The rise of MaaS breaks the issue by allowing passengers to monitor the chose transportation method on the cellphone, from booking to navigation, from credit payment to multi-transportation joint services. The MaaS has bring convenience to customers greatly.

In traditional MaaS systems, smart phone plays a significant role, which helps with ordering new trips, checking for timetables and paying for fares [9][10][11]. Smart phone is also able to collect real-time location information and movement trajectory continuously. Such mobility big data can be utilized for local passenger flow analysis and travel demand prediction, which can help transportation service providers automatically allocate capacities in specific time and locations. Thus, with the assistance of mobility big data, the MaaS system can be designed more ingeniously.

With the development of technology, collecting personal GPS data becomes simpler and more convenient, which shows great potential[12][13][14]. By extracting travel demands from real human mobility data based on GPS records, in this paper, we propose a novel MaaS shared bus system framework. Inspired by the ”last mile” scene, the system provides an efficient and environment-friendly solution for the short-distance movement around the subway station by arranging shared bus for different passengers. It is also capable of being deployed in other scenes in city transportations, including commuting scenes and tourist scenes.

To be more specific, optimal route of each shared bus is planned by establishing midway bus stations, which takes operating costs, the majority of the customers' demands and the uncertainty of punctual arrival into account. An ant colony optimization algorithm based method is developed to solve the route planning problem. The system is also capable to receive temporary requests raised by users through smartphone application.

More than this, we provide a real case experiment to test the efficiency of the shared bus system. We extract commuting demands between communities around subway stations and the stations. Based on the real travel demands, we analyze the environmental pollution that can be reduced to demonstrate the significance of our proposed system.

Our contribution includes but not limit to:

1. We develop a novel MaaS shared bus sub-system framework, which can optimize bus routes based on passengers' travel demands.
2. We extract real passengers' travel demands from big mobility dataset to test the efficiency of the shared bus system.
3. We analyze the reducible pollution in the real case to demonstrate the potential of shared bus system. We also explore how will different parameters affect the system performance.

The organization of the remaining sections is:

- Chapter 1 illustrates the background of the thesis and the related works of our problem.
- Chapter 2 describes the details of our proposed problem.
- Chapter 3 illustrates the proposed methodologies.
- Chapter 4 illustrates the experiment designs and the experiment results analysis.
- Chapter 5 illustrates the conclusions and future works.

1.2 Related Works

The Vehicle Routing Problems (VRPs) help identifying routes for a set of customers with fixed positions [15], and on this basis some further problems like the Vehicle Routing Problem with Time Windows (VRPTW) and The Dial-a-Ride Problem (DARP) derive from the original VRP[16][17]. The series problems first started with the famous Travelling Salesman Problem(TSP), described as given a list of cities and their distance graph, find a shortest route to cross all the cities then returns to the place of departure with no other repetitive visit[18][19]. Tadei *et al.* and Huang *et al.* explored stochastic conditions of TSP and VRP respectively, showing the path selection leads to significant savings of costs[20][21]. Then with the rise of more customer requests and travel demands, new problems and solutions generated in the fields of time constraints, travel economy and order appointed multiple destinations, etc. In 2010s, the sharing economy soon spawned the appearance of new public transportation methods like hitch rides and the shared taxi[22][23]. Nasser [24] summarized the exact, heuristic and metaheuristic methods to solve VRPTW.

In the field of customized bus service, with multiple starting points and a single destination, typically the problem can be summarized as a School Bus Routing Problem[25][26]. Schools in some countries offer school buses to pick up students from their homes to school in the morning and bring them back after school in the afternoon. The buses are not able to pick up the kids directly from the front door of separate houses due to time costs and economy, thus the kids' home positions are collected by the school bus office ahead of schedule, usually in the beginning of every semester. Then multiple bus stations are selected for communities in which one or more kids are living with different pickup time allocated for each station.

However, these methods of early decide origin-destination pairs are not appropriate in public transportation traffic flow predictions. If samples of real-world user trajectories are collected and processed to obtain authentic demands in subway-station nearby areas, new travel services may be released for commuters to solve the home-station transportation issues. Chen *et al.*[27] proposed an approach for bidirectional night-bus route planning based on a spreading algorithm. Tong *et al.*[28] proposed a joint system considering the optimization of both passenger-to-vehicle assignment and vehicle routing. Engelen *et al.*[29] presented a new method of dynamic insertion for buses combining a demand forecast algorithm to effectively reduce the rejection of passengers and the waiting times. Guo *et al.*[30] proposed a time-dependent urban bus routing methodology explicitly considered the flexibility of paths with a hybrid meta-heuristic algorithm. Kong *et al.*[31] designed a two-stage approach for subway shuttle bus route planning, composed of travel requirement prediction and dynamic route planning. However, the researches on customized bus for subway shuttle scenarios are rare particularly considering the high standard of customer comfort, let alone the emission analysis comparing to typical transportations. These elements are vital in the development of modern MaaS system and urban transportation construction, which is exactly emphasized in our article.

第 2 章

Problem Description

In this chapter we intend to make a brief description to our problem. The overview of our problem can be summarized as Fig. 2.1.

The Fig. 2.1 demonstrates two different patterns in bus operation modes. The bus starts from the depot near high traffic flow targets, say train station for instance, at 7:00. Both buses in pattern one and pattern two receive five candidate passenger requests. In Fig. 2.1(a), the bus abandoned the passenger 5's request at 7:20 and chose to pick the other four passengers continuously, while in Fig. 2.1(b), the bus chose a new route with a complete different visit sequence of the passengers because of the change in expect pick-up times.

(a)Bus operation pattern one

(b)Bus operation pattern two

Fig.2.1: Overview of the MaaS Shared Bus System.

Our goal is to provide shared-bus service for dense passenger flows to efficiently commute from subway stations to their destinations. Passengers getting off from trains in subway stations can take our service for the rest parts of their trips by providing their destinations and expected arrival time. We assume that each bus serves in a certain period.

To optimize the bus route, the first step is to decide midway bus stations, which should be considered thoroughly to reduce the walking distance of passengers and guarantee the restriction of expected arrival time. Since some of the passengers may alight in the same area or district, not all the destinations are chosen as midway stations. Then an optimal route should be planned based on the results derived from the first part, which is an one-origin multiple-destination vehicle routing problem. The vehicle starts from one starting station at a given time, each vehicle containing dozens of passengers heading to different destinations, and some of the passengers are supposed to alight at the same station at the same time. Each mid-way bus station will be passed only once, and every mid-way station will be attached to a certain alight time.

Assume that $U = u_1, u_2, \cdots, u_k$ denotes the group of k passengers that get off from trains and choose to take our service for the rest parts of their trips, their corresponding destinations $D = d_1, d_2, \cdots, d_k$ and expected arrival times $t_1, t_2, \cdots, t_k$ could be collected. A graph $G = (V, E)$ is utilized to represent distance relations between starting point of the bus and destinations, where $V = D \cup p_s$, p_s is the starting point of the bus and E is the shortest distance between two points on the road network. The bus route consists of n stations $S = s_1, s_2, \cdots, s_n, s_i \in V$. In particular, the first station and the last station are both the starting point, i.e., $s_1 = p_s, s_n = p_s$. The standard speed of each bus can be represented as v. For a given departure time t_0, the arrival time of each station $t_1, t_2, \cdots, t_n$ could be computed iteratively by:

$$t_i = t_{i-1} + \frac{E(s_{i-1}, s_i)}{v}, \forall i \in [1, n] \tag{2.1}$$

In addition, it is not proper to let passengers arrive too early or too late. We set a tolerance time Δt to represent the maximum difference time between the arrival time that passengers could tolerate and their expected arrival time. Then for any passenger u_i who expect to get off at station s_j at t'_{u_i}, we have:

$$t'_{u_i} - \Delta t \leq t_j \leq t'_{u_i} + \Delta t, \forall u_i \in U \tag{2.2}$$

Meanwhile, the passengers may get absence from the scheduled pick-up position. We use a punctuality coefficient θ_p to evaluate the possibility of arrival in-time.

Obviously, it is impossible to carry all passengers under the restrict limitations. So we set up an objective function to maximize the passengers to be delivered through the bus system, ultimately maximize the income of the service provider, which can also be achieved through decreasing the mileage of the buses. Thus, we utilize both passenger numbers and path length as the optimization parameters to establish the objective function.

第 3 章

Methodologies

In this section we tend to formulate an overview of the methodologies. We discuss the route planning procedure and the detailed algorithms used under the base of ant colony algorithms.

3.1 Ant Colony Optimization

Ant colony optimization is a meta-heuristic algorithm, designed specifically for solving combinatorial optimization problems. This probabilistic technique was inspired by a nature phenomenon that some ants wandering on the ground randomly to search for food, and when the food is found, they will leave pheromone on the trail back to their nest. The successors then prefer to follow the trail rather than move randomly, while reinforcing the concentration of the pheromone. The pheromone evaporates overtime, reducing its attractive strength gradually if the ants who follow the trail failed to bring back food continuously.

The original ants may take two separate paths from the same start to the same destination. Assume that ants all move in the same speed, ants who take the longer path will cost longer time. The pheromone left in the longer path is supposed to evaporate more than other trails, leading the possibility of choosing the shorter path higher for the next ant. Through iteration, ants will eventually find the shortest path between destinations. In our problem, the ant system is described as following:

1. Ants are moving around on the road network as shared buses, and each ant has speed

limitations in different roads according to local laws.

2. Each ant that successfully delivers passengers to their destinations is considered as s-ant, no matter how many passengers they delivered in total.
3. The pheromone left by each s-ant is computed according to multiple indexes, including the total distance the ant went through and the number of delivered passengers.

The pheromone will be updated after each iteration. The old pheromone will evaporate by a ratio set in advance, and then the newly generated pheromone will be added. In the first batch, an amount of N ants will be deployed to the original station, and since no former information is given, the possibilities of moving to station V_i is:

$$P(0, i) = \frac{1}{m}, \forall i \in [1, m] \tag{3.1}$$

After the first batch, some routes are evaluated with higher pheromone for shorter path and more delivered passengers. In the next turn, these stations will be more easily chosen as the next station than other stations. After each iteration, pheromone is updated according to the ant that delivered the most passengers to their destinations within the shortest path. For iteration k among the total iteration times M, assume the best ant has a route:

$$R_k = \{W_1, W_2, W_3, .., W_n\}, k \in (1, 2, 3 \cdots M), W_n \in V \tag{3.2}$$

The total number of delivered passengers is:

$$Pas_k = \sum_{i=1}^{n} D(W_i) \tag{3.3}$$

The total distance of path is:

$$Dis_k = \sum_{i=1}^{n-1} d_{i,i+1} \tag{3.4}$$

Then the new pheromone graph is updated by:

$$Phe(V_i)_k = \begin{cases} Phe(V_i)_{k-1} \times \mu + \frac{Q \times D(V_i)}{Dis_k}, & \text{if } V_i \in R_k \\ Phe(V_i)_{k-1} \times \mu, & \text{if } V_i \notin R_k \end{cases} \tag{3.5}$$

The coefficient Q tends to balance the influence from the passenger number and the total distance of the path. Since after each iteration, existed pheromone will evaporate a certain percentage, the proportion of the surplus pheromone is denoted by μ. After adequate iterations, the ants will gradually find the most efficient path to deliver the most of the passengers within their time constraints, while taking the shortest route.

3.2 Ant Route Search Algorithm in ACO

Algorithm 1 Single Ant Route Search Algorithm $FindRoute(G(V, E), Phe[V_i], t_0)$

Require: The graph of distance between each pair of candidate positions $G(V, E)$; The expected arrival time of each candidate t_i; The pheromone graph $Phe[V_i]$; The start time of the ant t_0; The maximum time difference between actual arrival time and expected arrival timeδt_{max}; The ant speed v.

Ensure: The delivered passenger number n and the path $Path$

Set an array $table_i \leftarrow True$ for each candidate, $n \leftarrow 0$, $Path \leftarrow Empty$, temporary time $t \leftarrow t_0$

// Find a path to deliver passengers

while $table$ not all $False$ **do**

  Randomly pick i in open-table if $Phe[i] = True$

  $\delta t = \frac{E(V_i, V_{temp})}{v}$

  if $|t + \delta t - t_i| \leq \delta t_{max}$ **then**

    $n+ = 1$

    $t+ = \delta t$

    $Path.append(V_i)$

    $table_i = False$

    $V_{temp} = V_i$

  end if

end while

return $n, Path$;

Each ant follows the Algorithm 1 to move step by step until it no longer finds a feasible candidate position, under the strict time-window restrictions and the influence from the past pheromone to the surrounding environment. However, a single ant may not be able to discover the global optimal solution, thus adequate ants are necessary. The algorithm 2 describes the top-level conceptual model of ant dispense and pheromone update.

3.3 Pheromone Update Algorithm and Global Best Route Search Algorithm in ACO

For the punctuality of the passengers, we use a concept of passenger pool to describe this part. The passenger pool includes a certain number of passengers, each passenger in the pool is a candidate, and have attributes of:

1. Request pick-up time
2. Request pick-up position
3. Expect destination subway station
4. Maximum tolerance time
5. Punctuality of arrival

The punctuality is used to describe whether the passenger can arrive at the request pick-up position in time. The passenger pool is dynamic for real-time update, especially the punctuality before the depart of the bus. When the punctuality of a passenger is too low, the passenger may be absent with high probability, thus be deleted from the candidate passenger pool. In our proposed algorithm, the pheromone update is decided by the actual served passenger number rather than responded requests number. The result of our algorithm then will converge to choose those passengers with high possibility of punctuality.

Basically, we make improvements on traditional ACO algorithm in ways below:

1. We use the time consuming for the ant from one node to another to restraint the waiting time of the passengers, and thus guide the route searching regulations of the ants
2. We add the passenger punctuality into consideration, the visited positions and the picked-up passengers are calculated respectively. In pheromone update procedure and the best ant searching, we use the ant with the most delivered passenger number as an objective

Algorithm 2 Pheromone Update and Best Route Search Algorithm

Require: The graph of distance between each pair of candidate positions $G(V, E)$; The number of ants s; The start time of the ants t_0; The pheromone graph $Phe[V_i]$; The iteration times M The evaporate ratio μ

Ensure: The delivered passenger number n and the path $Path$

Initialize pheromone graph $\forall Phi[V_i] = 1, n \leftarrow 0, Path \leftarrow Empty$
// In iteration times, generate n ants, each ant finds its best route
for $k = 1$ to M **do**
    // Iteration times
    for $j = 1; j < s; j++$ **do**
        // Ant number
        $p, Path_{tmp} = FindRoute(G(V, E), Phe[V_i], t_0)$
        if $n \leq p$ **then**
            // Update global optimal result by different standards.
            // The n can represent the visited station numbers or the actual onboard passenger numbers, considering the certainty of punctual arrivals of the customers
            $n = p$
            $Path = Path_{temp}$
        end if
    end for$Dis_k = \sum_{i=1}^{len(Path)} d_{Path[i],Path[i+1]}$
    //Pheromone Update by temporary best route
    for $\forall \mathrm{V}_i$ **do**
        if $V_i \notin Path$ **then**
            $Phe[V_i] *= \mu$
        end if
        if $V_i \in Path$ **then**
            $Phe[V_i] = Phe[V_i] * \mu + \frac{Q * D(V_i)}{Dis_k}$
        end if
    end for
end for
return $n, Path$;

function.

These improvements in ACO makes it possible to analyze the influence made by our proposed scenario: passengers have different punctuality. These methods help us to balance between not leaving the passengers with a much longer waiting time and maximizing the income of the bus operator companies by picking up the most number of the passengers.

第 4 章

Experiment Result and Analysis

In this section, we test the robustness of the proposed system under a real-world scenario. Then We test the flexibility of our system by considering possible changes in real-world operations. We also analyzed our proposed system with the uncertainty of punctual arrival of the passengers. Finally, we analyze the environmental pollution that can be reduced to highlight the importance of a well-designed shared bus system.

4.1 Experimental Set up

A real world scenario is usually in a large or mega city with multiple transportation modes. To construct the benchmark, we extract passengers' travel demands from a big mobility dataset in Tokyo, Japan. The original dataset is a part of “Konzatsu-Tokei (R)” Data provided by Zenrin DataCom INC. “Konzatsu-Tokei (R)” Data refers to people flows data collected by individual location data sent from mobile phone under users' consent, through Applications provided by NTT DOCOMO, INC. Those data is processed collectively and statistically in order to conceal the private information. Original location data is GPS data (latitude, longitude) sent in about every a minimum period of 5 minutes and does not include the information to specify individual[32][33]. ※ Some applications such as “docomomap navi” service (map navi・local guide).

After several pre-processing including map matching, travel mode detection and stay point clustering, we collect the crowd flow, in which people just get off the subway and tend to move to next destination. Considering the size of our raw dataset, we pick five major subway stations and their surrounding areas in Tokyo, Japan as target study sites: Ikebukuro, Shibuya, Shinagawa, Shinjuku and Tokyo. The morning peak between 7:00 am and 8:00 am is selected as target period. Of each station, the crowd flow involves more than fifty-thousands' passengers in the target period. The Fig. 4.1 demonstrates the distribution of the samples in our dataset. The red dots are part of the locations of the train stations in Tokyo city, while the green points are the collected requests near the stations. The five red dots with outer black circles are the chosen 5 stations.

Fig.4.1: The distribution of the dataset and the studied stations.

Based on the mobility pattern of the crowd flow, we sample and generate passengers' requests for taking bus, in which their expected arrival time are set as their ground truth arrival time. We set the default request number of each bus as 20. If requests are too many for a single bus, one delivery turn will take more than 40 minutes, making some of passengers wait too long on the bus. On the other hand, less requests lead to less income for operators while the operating expense decrease inconspicuously.

The default tolerance time for passengers is set as 3 minutes. The tolerance time can be set longer if we intend to deliver more passengers, or shorter if we intend to provide the most precise service for passengers. More information about the practical operation can help to optimize the benefits of our service.

The default number of buses is set as 3, which means three buses can carry passengers at the same time. The target period is divided into 6 slices with 10 minutes. As shown in Fig. 4.2, three buses set out alternately and get back to the subway station after all passengers being delivered. Then the bus pick up another batch of passengers and and set out at the beginning of next ten minutes slice. For instance, a bus sets out at 7:00 am, at which time it carries passengers whose expected arrival time is in the 0-10 min slice,10-20 min slice or 20-30 min slice. After delivering all passengers and getting back at 7:35 am, the bus sets out again at 7:40 am to deliver new passengers whose expected arrival time is between 7:40 am and 7:50 am.

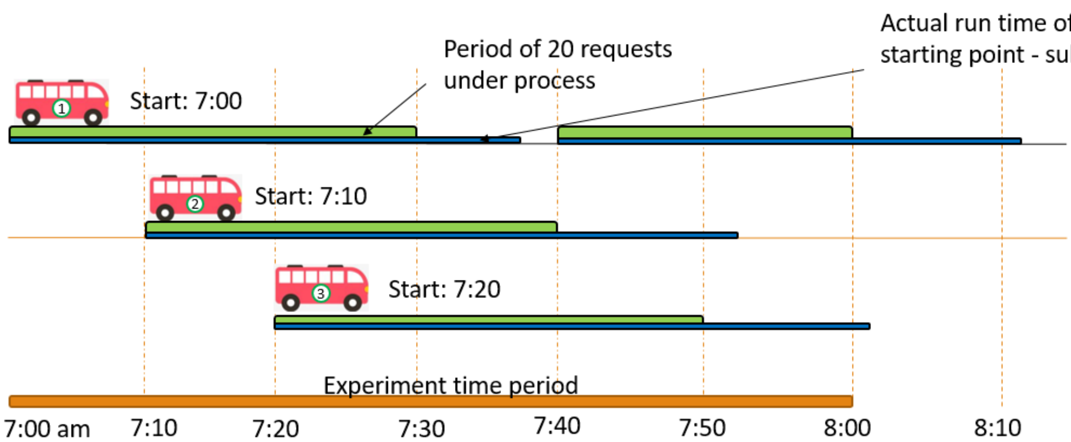


Fig.4.2: The operation patterns of shared buses.

The experiment is conducted on a PC with 8-core 4.0GHz CPU and 16 GB of RAM, using Google Map as a demonstration board and all results are stored in a look-up table.

4.2 Experimental Results and Analysis

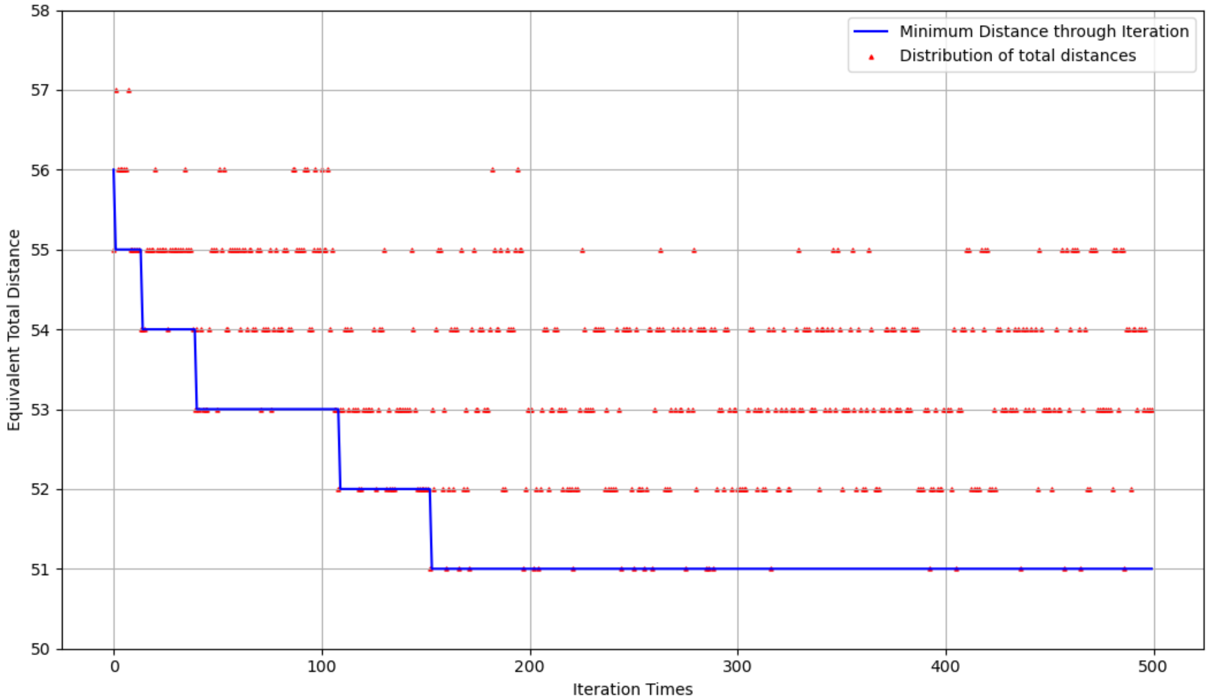
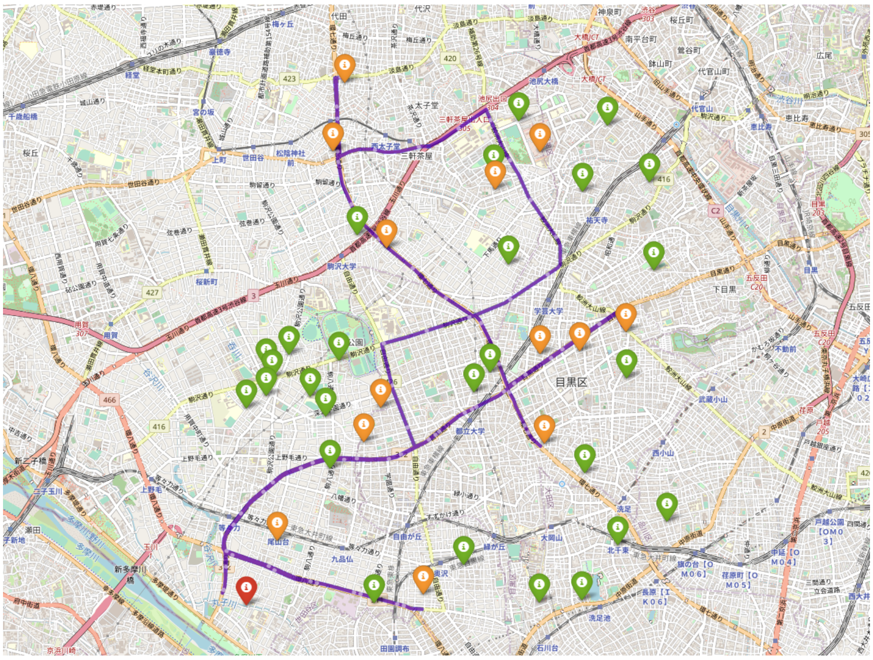
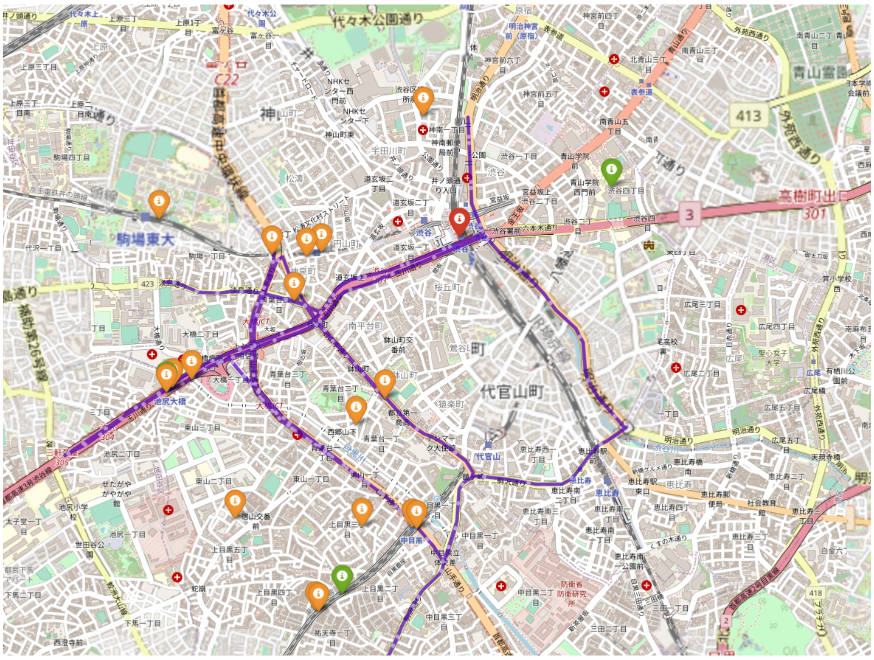


Fig.4.3: The results of ACO by iteration.

The Fig.4.3 reveals the convergence of our proposed ant colony optimization method. We recorded the outputs of 500 iterations with 50 ants generated in each run, and the input for our model are 20 requests, which was extracted randomly in the dataset of Ikebukuro station. In Fig. 4.3, the small red triangles are the outputs of the equivalent distances, since we use the consumed time to replace the expression of total distance. We can see that the algorithm gives an initial result of 56, and through iteration the minimum value declined to 51 after around 150 iterations. After that, the results tend to be stable. The changing curve prove that our algorithm is capable of solving the proposed problem and performs a valid optimal effect in discovering a shortest route.



(a)Simulation case



(b)Real-world case

Fig.4.4: Examples of planned bus routes.

Fig.4.4 visualize two simulated routes of a bus as an example. The red mark denotes the starting point of the bus, which is also the subway station. Each green and yellow mark represents a request from one person. The yellow marks are passengers that are successfully delivered, and the green marks represent people who cannot be sent in time and are not served. The purple line denotes the route of the bus. In Fig. 4.4(a), we randomly generated 50 travel demands with different positions as destinations in Tokyo city, and also randomly set their expected arrival time within one hour to examine the validity of our route planning algorithms. Fig. 4.4(b) demonstrates the planned route of 20 real requests around Tokyo station.

Tab.4.1 reveals two metrics to measure the performance of the system for different stations, including delivery ratio and time difference. Delivery ratio is defined as the number of delivered passengers dividing the total number of requests. Time difference denotes the absolute value of the difference between actual time of delivery and passengers' expected arrival time.

Under default conditions, the average delivery ratio varies from 0.159 in Shinagawa station to 0.329 in Shinjuku station, mainly caused by indeterminacy factors like the distribution distinction of the requests between different stations. The average time difference in different stations is relatively similar, which verifies the consistency of our algorithm.

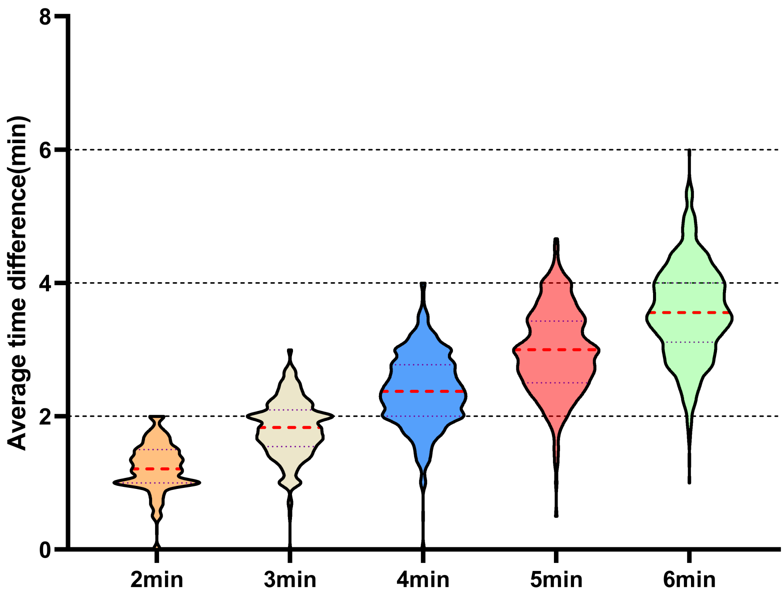
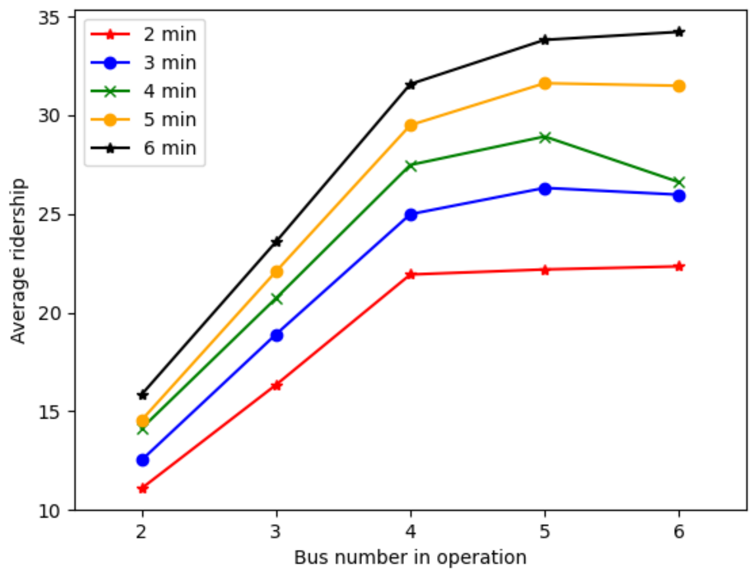
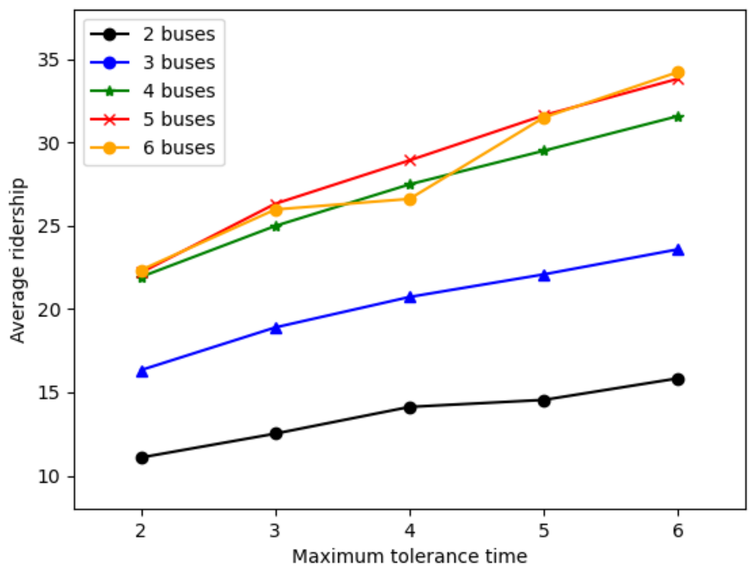


Fig.4.5: Distribution of results under 2 to 6 minutes maximum tolerance time. The thick red dotted line represents the mean value, and the thin red lines represent the quartiles.

When the maximum tolerance time gets longer, it is obvious that delivery ratio and time difference both increase. On the one hand, longer tolerance time gives the bus higher fault tolerance rate, which makes it possible to carry more passengers; on the other hand, more passengers inevitably make the average waiting time longer. Fig. 4.5 demonstrates the violin plot of the average time difference distribution with different maximum tolerance time. From the figure we can see that the average time difference usually lies at around half of the maximum tolerance time, which proves that our algorithm can effectively ensure the delivery time.



(a)Average ridership with different number of buses



(b)Average ridership with different maximum tolerance time

Fig.4.6: Average ridership with different number of buses.

We also visualize the change trend of average ridership (or delivered passengers) with different parameters in Fig. 4.6. In (a), the number of buses is different. As more buses are put into use, more passengers will be delivered, which is observable when bus number is less than 4. However, when more than 5 buses are put into use, the final bus starts at 7:40 due to our preset bus operation patterns, so it will only receive passenger requests between 7:40 and 8:00, which is 10 minutes less than former buses, thus carrying less passengers. In (b), the maximum tolerance time is different. Similar with Tab. 4.1, the increase of maximum tolerance time makes the buses possible to carry more passengers, and the sufficient tolerance time leads to stable increase in final ridership.

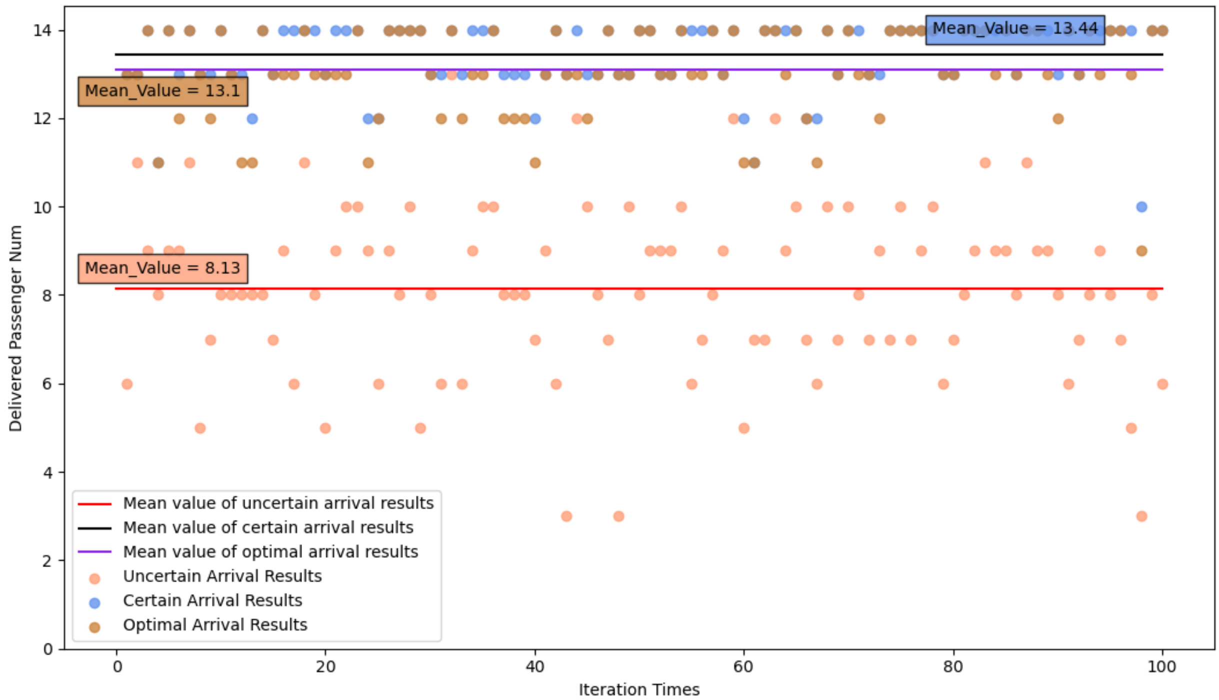


Fig.4.7: Distribution of results under uncertain passenger punctual arrivals and certain punctual arrivals.

We analyze the performance of our model in the dimension of passenger punctuality. The Fig. 4.7 reveals the distribution of the results with uncertain and certain punctual arrivals of the passengers. In Fig. 4.7, we tested the ridership of one bus with 40 passengers. In each test, we generate results of:

1. Experiment of 40 passengers with certain punctual arrival using incipient ACO algorithm
2. Experiment of 40 passengers with uncertain punctual arrival using incipient ACO algorithm
3. Experiment of 40 passengers with uncertain punctual arrival using optimal ACO algorithm

The 40 passengers remain the same in each test as input. The certain punctual arrival denotes that the passengers can always arrive at the designated pick-up position, and in uncertain punctual arrival scenarios, we give each passenger a possibility of punctuality, a random number between 0.5 and 1.0. The blue dots in Fig. 4.7 represent the experiment result of certain punctual arrivals. We can see the delivered passenger number fall in between 10 and 14 when all passengers can arrive in time. But when the uncertainty is given, the ridership decrease sharply. The mean value of ridership decrease from 13.44 to 8.13. When we use the optimal ACO algorithm to take the uncertainty into account beforehand, the mean value rocket to 13.10, which was close to the result of certain punctual arrivals. This shows that our proposed method can effectively operate to deliver the most number of passengers under various real-world scenarios, bringing the best service quality for customers and the highest earnings for operators.

Fig.4.8: (a)average MaaS bus CO emission in grams while using gasoline, (b)average MaaS bus NMHC emission in grams while using gasoline, (c)average MaaS bus NOX emission in grams while using gasoline (d)average MaaS bus PM emission in grams while using gasoline, (e)average MaaS bus CO emission in grams while using diesel, (f)average MaaS bus NMHC emission in grams while using diesel, (g)average MaaS bus NOX emission in grams while using diesel, (h)average MaaS bus PM emission in grams while using diesel,(i)average car CO emission in grams while using gasoline, (j)average car NMHC emission in grams while using gasoline, (k)average car NOX emission in grams while using gasoline, (l)average car PM emission in grams while using gasoline

Then we compute and compare the traffic pollution generated by shared bus and private car. The emission standard we use is from the regulation made by Ministry of the Environment [34]. We use the emission standard made before 2009 and the trajectory data is from 2011. Therefore, all of the vehicles meet the standard. The emission standard provides the general emission coefficient that can be utilized to compute the quantity of pollutants including CO, NMHC, NOX and PM based on the travel distance. In this study, we use 1.92 g/km (CO), 0.08 g/km (NMHC), 0.08 g/km (NOX) and 0.007 g/km (PM) as the emission coefficient for private cars and gasoline buses; 0.84 g/km (CO), 0.032 g/km (NMHC), 0.11 g/km (NOX) and 0.007 g/km (PM) for diesel buses.

As shown in Fig. 4.8, we separately compute the emissions of our shared bus using gasoline and diesel as energy source, and then compute the emission of a scenario that if all potential passengers move to their destinations by private gasoline cars. The numeric results are the average of 300 times 3-bus operations with requests between 7:00 am and 8:00 am in grams. The emission of Shinagawa case tends to be higher due to longer average operation distance, but opposite in average private car usage. Buses using diesel have a higher emission load than using gasoline in NOX, but less in CO, NMHC and PM emission. However, no matter which kind of energy supply is used for buses, the pollution is much less compared to gasoline cars in all metrics.

Table4.1: Experimental results with different maximum tolerance time

		Ikebukuro	**Shibuya**	**Shinagawa**	**Shinjuku**	**Tokyo**	**Average**	**Variance**
2min	Average delivery ratio	0.243	0.253	0.117	0.286	0.232	0.230	0.016
tolerance time	Average time difference(min)	1.218	1.251	1.231	1.230	1.238	1.233	0.136
3min	Average delivery ratio	0.324	0.291	0.159	0.329	0.267	0.279	0.017
tolerance time	Average time difference(min)	1.774	1.855	1.881	1.774	1.798	1.805	0.203
4min	Average delivery ratio	0.343	0.316	0.185	0.378	0.307	0.310	0.016
tolerance time	Average time difference(min)	2.259	2.433	2.521	2.334	2.426	2.371	0.304
5min	Average delivery ratio	0.390	0.346	0.213	0.387	0.331	0.337	0.016
tolerance time	Average time difference(min)	2.842	2.982	3.183	2.853	2.979	2.936	0.410
6min	Average delivery ratio	0.398	0.380	0.255	0.424	0.363	0.367	0.014
tolerance time	Average time difference(min)	3.440	3.540	3.894	3.414	3.528	3.528	0.481

第 5 章

Conclusion and Future Works

5.1 Conclusion

In this paper, we propose a shared bus system for commuters delivery with meta-heuristic methods to solve the route planning problem. We take the punctuality of buses into consideration to explore the delivery quality under different maximum tolerance time. We also take the punctuality of the customers into consideration to explore the effectiveness of our system under different scenarios. Our service is tested by extracted real-world travel demands in Tokyo to demonstrate the robustness and feasibility. Compared with normal travel by private cars, our bus service is environmental friendly, producing much less emission in CO, NMHC, NOX and PM.

The contribution of this paper includes:

1. We proposed a modified algorithm basing on the original Ant Colony Optimization method to accommodate different customer demands indexes like the waiting time of the passengers in bus sharing industry.
2. We take the punctuality of the customers into consideration to verify our algorithm under the demonstrated scenario, leaving further possibilities in future collaborative designs.
3. We explored the relationship between bus ridership and passenger waiting times, trying to find a balance between ridership and customer satisfaction.
4. We use real-world travel demands to examine the feasibility of our proposed bus-sharing system. Our simulation shows that our proposed modified ACO algorithm can largely increase the ridership of the buses compared with original ACO.

We used real-world data collected from different railway stations in Tokyo city in order to eliminate the influence of randomness, and our results also verified the feasibility of our designed process.

5.2 Future Works

Still, this work is the early stage of MaaS guided shared transportation services. It remains space for improving the algorithm in promoting the accuracy in station-path matching and decreasing the possibilities of detour. One other optimizing direction is to take both delivering and picking up services into consideration to advance the income of bus service operators and also provide more comfortable services for commuters.

Another aspect of our future direction is the passenger punctuality prediction. In our work the discussion of this part is partly based on our assumptions and simulations. With more authentic data of passenger demands and other supplementary information to get the punctuality with higher accuracy, the system may get better designs and become more convincing.

Our aim is to maximize the passenger delivered for bus operator companies, but when we consider our scenario is the customers' prospective, we may switch to enhance the comfort level for passengers. For example, we may set the truck to reach at the destined railway station before a certain time so that the passengers can catch up the train. Meanwhile, decreasing the total operation time for passengers to stay on the bus is another way to improve the comfort of the customers.

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May the world stay in peace without wars.

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