A SIMULATION OF OPERATION OF DEMAND RESPONSIVE TRANSPORT BASED ON REAL DATA OF ROAD NETWORK AND POPULATION DISTRIBUTION ON GIS*

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1. Introduction

This paper focus on building simulation of Demand Responsive Transport (DRT) service in a rural area. The paper begins with discussions of simulating the operation of DRT. In simulation, the population distribution by each mesh has been used to generate the demands. The Ant Colony algorithm brings an optimized spatial route layout in draft. Then, the Shortest Path Algorithm is applied to the real road network to get various results with alternative routes.

2. The Demand Responsive Transport

(1) Transport System between Private and Public Transport

The private and public transports have been coexisted for hundreds of years. The private transport gives individuals the maximum flexibility of travel but it is not efficient from the system point of view. That has also been observed in disordered physical systems. Public transport then appeared based on the increase of public Information symmetry. Public transport can dramatically save the system cost but it dropped much flexibility from the individual point of view. As the information technology advanced, DRT system arose firstly in rural area as the effective solutions where public transport demand is sparse[1)]. There is a promising way of DRT in the near future that will compensate the blank left by public transport and private transport in cities. (Figure1)

(2) Necessity of Simulation in Computer

Although introduction of DRT in rural areas has some advantages, it is necessary for planner to estimate its economic and social effects as well as its operation. One of the effective methods is building a simulation model on computer. Existing researches rarely use real road networks for simulation because of their complexity. Most of them use small ideal networks for testing and then intend to derive the general results from the networks[2)]. There may expand the small errors to not understandable results. This study not only uses the real road network but also the surveyed population distribution by each mesh to consider real situation on the simulation. To decrease the complexity of the simulation, three steps of the whole procedure consist of: 1) Extracting Demand from Population Distribution, 2) Optimizing Layouts of Routes and 3) Calculating Detailed Routes in Real Road Network.

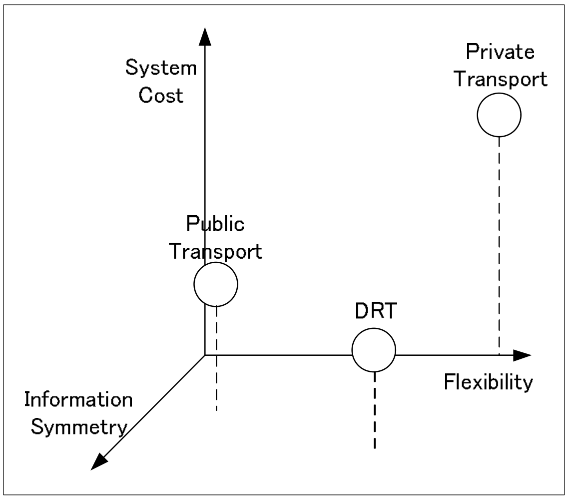

Figure 1: The Relationship among Private Transport, Public Transport and DRT

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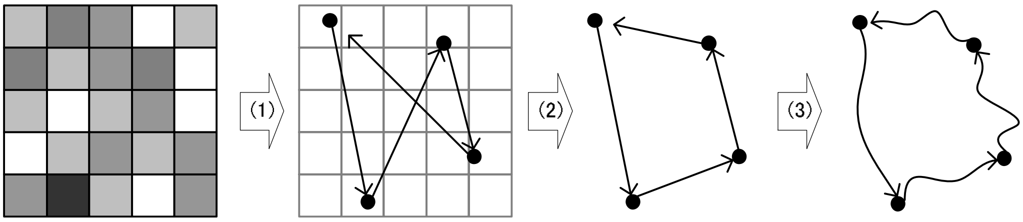


Figure 2: Steps of Simulation

3. Simulating the Operation of DRT

The research area is Tahara city in Aichi prefecture. It has 188.58km^2 area where 66,743 people are living (2007). There are four statuses that the simulation can achieve. Between the four statuses the three steps have been performed which mentioned above (Figure 2). In the initial status, population distribution by each mesh should be loaded in GIS. Then use it to generate the demands in which the start point is always fixed. In the second status there are links indicate that the vehicle gets off from the start point then picks up the demands in order. The third status will be gotten after optimizing the layout of routes. The road network will be employed to calculate the specific routes and various results. To simplify the spatial and network analysis, MicroCity[6)] is used as the simulation platform. The following will elaborate the three steps in the transitions of the four statuses (Figure 3).

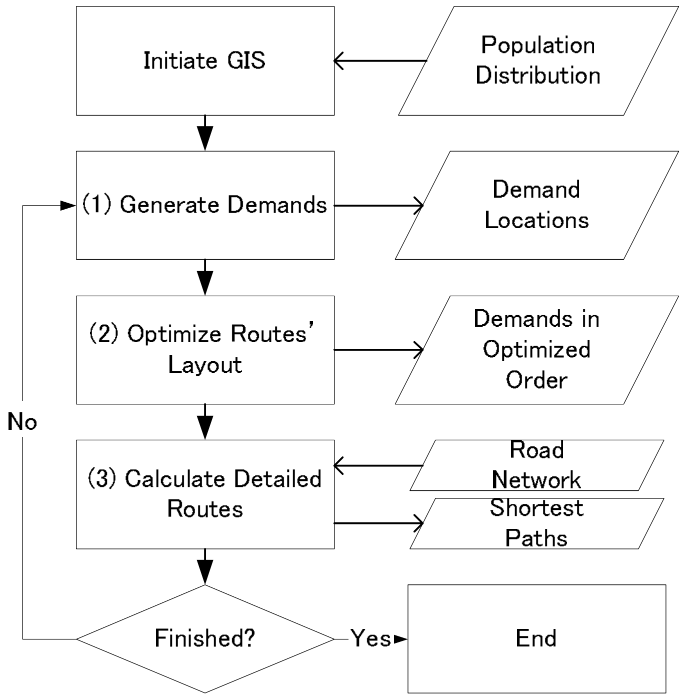


Figure 3: Abstract Flowchart of the Simulation

(1) Extracting Demand from Population Distribution

The surveyed population distribution had been stored in GIS (Figure 4). The width of the mesh cell is 500 meter. To generate the demand accounting to the population distribution, the Roulette Selection Method is used, in which population number in every mesh cell need to be aligned in an order, then choose a number randomly and check the corresponding cell. Demand locations in cells related to population distribution are also decided by using random method. A higher density of population will cause a higher frequency of demand. In the beginning of every loop, demands are regenerated in this way to ensure the diversity of the simulation.

(2) Optimizing Layouts of Routes in Spatial Distance

All demands data generated from (1) are saved in the order of its generation order. But if a vehicle picks up passengers by this order, that will be very inefficient. The routes will overlapped heavily and the total travel time will become very large. It is necessary to optimize the travel route plan before allocation of a vehicle to run along it. From existing researches the Ant Colony algorithm maybe the suitable solution for this purpose. Ant Colony optimization algorithms have been used to produce near-optimal solutions to the traveling salesman problem. They have an advantage over simulated annealing and genetic algorithm approaches when the graph may change dynamically; the ant colony algorithm can be run continuously and adapt to changes in real time. This is of interest in network routing and urban transportation systems.

Applying Ant Colony algorithm to a complicated road network may consume much simulation time. This study tried to optimize the spatial layout of the routes without employing the road network. It is easy to find out that if the road network is complex enough the length of the layout route can be very close (up to 80%) to the real route between two points.

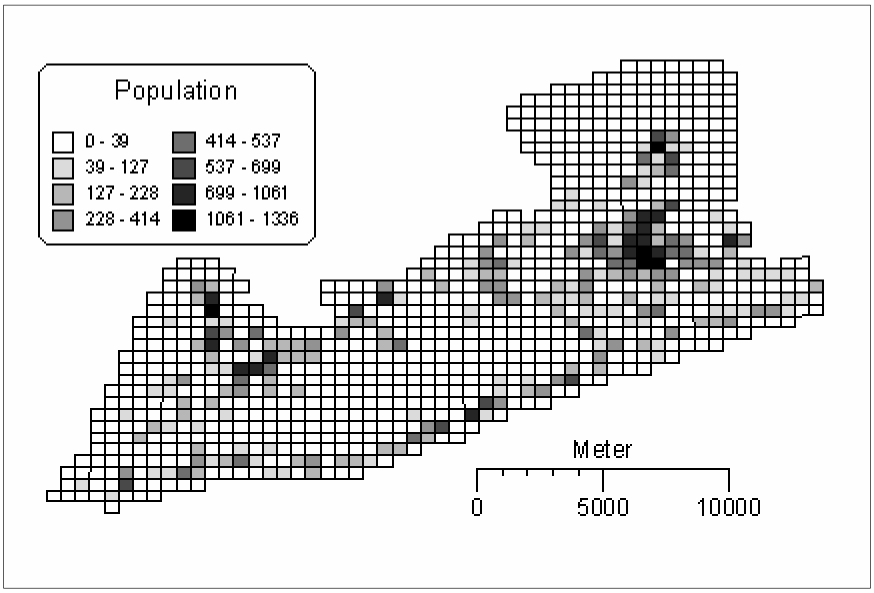


Figure 4: Population Distribution in the Research Area

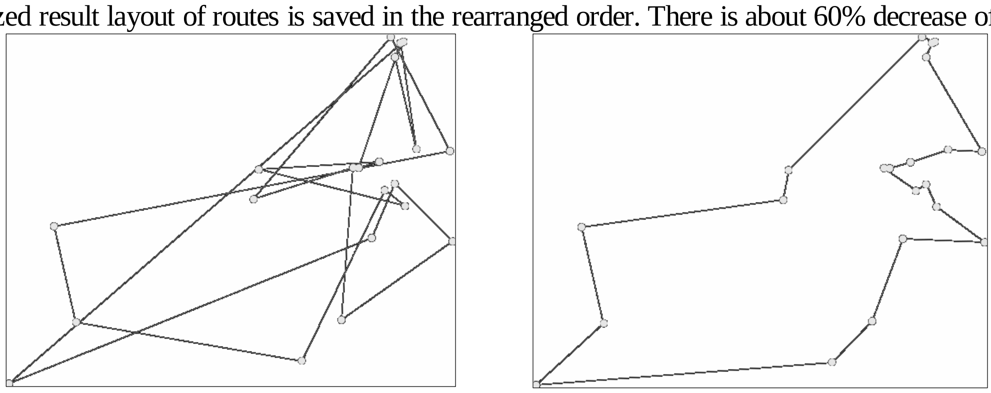
To improve the optimization speed, this study applies a multi-agent system as the running platform of Ant Colony algorithm[5]. The data of the layout routes imported to this system as a graph (Figure 5). Each agent (i.e., ant) constructs a tour in the graph by making a choice at each node as to which node will be visited next according to a probability associated with each node. The probability P_{ij} of an ant choosing a specific node at any time is determined by the amount of pheromone and the cost (i.e., the distance D_{ij} from the current node i to the next node j, where node j has not yet been visited) associated with each edge. Let τ_{ij} be the intensity of trail and k as allowed node. The transition probability can be presented as

$$P_{ij} = \frac{[t_{ij}]^{a} \cdot [D_{ij}]^{-b}}{\sum [t_{jk}]^{a} \cdot [D_{jk}]^{-b}} \tag{1}$$

The attributes in this method that can be adjusted to change the behavior of the algorithm are α, β, and ρ. The α and β values are used to determine the transition probability discussed above, where the values are used to adjust the relative influence of each edge's pheromone trail and path cost on the ant's decision. A ρ value is also associated with the algorithm and is used as an evaporation rate which allows the algorithm to "forget" tours which have proven to be less valuable.

Empirical evidence shows that the optimal settings for the algorithm are: $\alpha = 1$, $\beta = 5$, $\rho = 0.5$. This study tried adjusting each of these settings from the optimal and takes notice of how they affect the performance of the algorithm. The adjustments lead to a steadier march towards the best tour or perhaps they add up to a good initial search that settles quickly into a local optimum. The changes to the evaporation rate lead to stagnation.

The optimized result layout of routes is saved in the rearranged order. There is about 60% decrease of the original



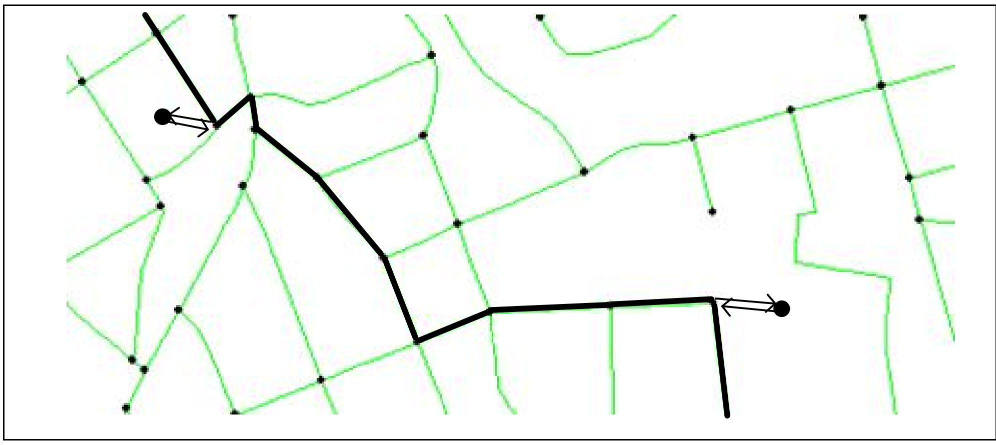
a) Before b) After

Figure 5: An Example of Routes' Layout before and after Optimization

routes' length after optimization.

(3) Calculating Detailed Routes in Real Road Network

The last step returned to GIS platform. Those rearranged demand points need to be relocated above the real road network. After topologizing the raw road network, every point has to find a nearest node in the road network. Then the Shortest Path Algorithm applied to calculate the detailed routes between these nodes (Figure 6). The direct link between demand points and their nearest nodes in the network should be taken account of as parts of the routes. Figure 5 shows the real road network and the travel times of several cruises that have been calculated based on it. Other indicators such like travel cost and requested number of vehicles can also been gotten afterwards.



Time 1	927.26
Time 2	862.21
Time 3	876.13
Time 4	969.41
Time 5	1002.33
Time 6	691.07
Time 7	769.69
Time 8	788.62
Time 9	735.94
Time 10	905.77
Time 11	768.08

Figure 6: A Part of a Shortest Path and Travel Time of Different Paths

4. Conclusions

This study constructs a DRT simulation model for real road network and population distribution on GIS. Because of the complexity of data and the heavy calculation, the simulation has been divided into four status and three operation steps. The method mentioned by this study has shown the efficiency on managing large data and controlling heavy calculation task. The characteristics of DRT were realized by using the simulation and evaluations can be performed based on the final simulated routes.

Currently this study assume that the demands occurred in a short time that only one vehicle can pick up them all. Actually the demands occurred continuously that the management of dispatch schedule needs to be taken into account. That means the time window should be used as constrains in optimizing the layout of routes and the simulation should be integrated more tightly.

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