Application of Community Detection Method to Generating Public Transport Network

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ABSTRACT

Scheduled liner service is a proper system for mass transportation and it is employed by wide range of transportation modes, such as bus, railway, airline, maritime transport. To get more ridership, providers of the liner service are required to organize efficient routes and networks of the service. This paper tackles the problem of generating Public Transport Network (PTN) as one of the liner services. Our method generating PTN is based on Multi Agent System, in which one agent represents one bus line with information of transit route and vehicle number. Although it successfully output best solutions for a benchmark problem, the solution and computation time depend on quality of transit routes of initial line set. In this paper, community detection method is applied to generate proper line routes and the original method based on a growing network model is replaced with it. The advantage and disadvantage of the community detection method are investigated.

Categories and Subject Descriptors

I.6.4 [Computing Methodologies]: Simulation and Modeling—Model Validation and Analysis

General Terms

Algorithms, Performance, Design

Keywords

Multi Agent System, Community Detection, Transportation, Public Transport Network

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1. INTRODUCTION

Scheduled liner service is a proper system for mass transportation and it is employed by wide range of transportation mode, such as bus, railway, airline, maritime transport. Service providers open their schedule (i.e. route path and time table) to users and users select efficient route for themselves. Thus, service providers are required to organize efficient transport network to increase their profit.

This paper focuses on public transport network (Hereinafter referred to as PTN) of bus as one of scheduled liner services. Generating PTN is a hard problem. Since the problem includes many elements influencing transportation performance (e.g. such as vehicle number, transit route, line number), classical method like mathematical programming faces many difficulties in the process of mathematical formulation and optimization. Furthermore, it easily leads to combinatorial explosion even though the number of bus stop is small. Most of previous studies attacking the problem rely on heuristic or meta-heuristic method [7].

We proposed Multi Agent System (hereinafter referred to as MAS) as an algorithm generating PTN [12]. One line composing PTN represents one agent (Hereinafter referred to as Line Agent) and it competes for passengers by evolving with changing route. Final solution as PTN is a set of line agents survived after the evolution process. However, solution of the developed MAS depends on transit routes of initial set of line agents.

There are many papers investigating community detection algorithm. Set of nodes connected by many links in networks is detected as community. Thus, node set detected as a community has potential to become an efficient transit route of the initial line agents of our MAS.

This paper is organized as follows. Problem of generating PTN is defined in section 2. Section 3 briefly explains a method with MAS generating PTN and community detection method. The analysis results are presented in section 4.

Section 5 investigates results of the analysis. Finally, section 6 gives conclusion.

2. PROBLEM DEFINITION

As a matter of convenience, transportation mode is set to bus line network in this paper. Thus, vehicle is bus, physical infrastructure network is street and nodes representing bus stops. All of the information on street network, position of bus stops, demand matrix that element is transport demand between two bus stops, vehicle speed and seating capacity are given. The demand matrix is often called as OD (Origin, Destination) matrix.

Solution is a set of bus lines that has information about route and vehicle number. The route of bus line is defined by a permutation of bus stops and it is assumed that the buses travel back and forth on the line. Furthermore, since express bus is not considered, vehicle stops at all bus stops on its route. Fig.1 shows an example of problem and solution.

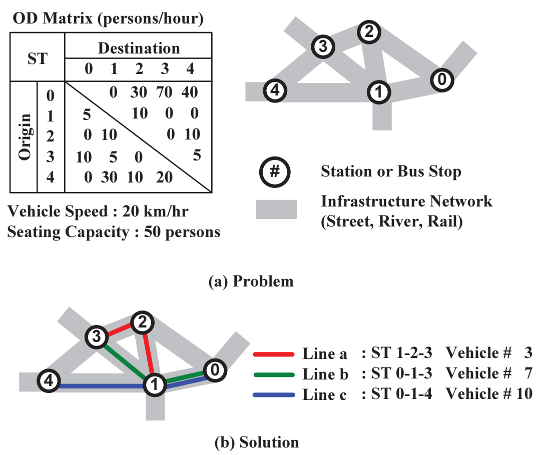

Figure 1: Problem Definition and Example of Solution

The evaluation function similar to the following equation is applied frequently to the problem of PTN [17]. In our MAS, the same evaluation function is employed.

$$\min Z = \sum_{S_i \neq S_j \in ST} T_{S_i,S_j} D_{S_i,S_j} + w_1 \sum_{L_k \in BL} B_{L_k} \tag{1}$$

Where, ST is set of bus stops, BL is set of bus lines, D_{S_i,S_j}, T_{S_i,S_j} are demand and traveling time from bus stop S_i to S_j respectively. The traveling time is composed of not only in-vehicle time, but also expected waiting time and penalty time for transferring. B_{L_k} is number of vehicle deployed into bus line L_k. The traveling time from bus stop S_i to S_j, is simply calculated by Euclidean distance on the street network and service speed of vehicle.

The first term in Eq.1 is user's cost and the second term is operator's cost. w_1 is control parameter. It is expected that small w_1 reduces traveling time and large w_1 reduces number of bus. Passengers hope to reduce the first term and transportation companies hope to reduce the second term. Generally speaking, relationship between two terms is trade-off relationship and it is one reason of the difficulties to solve the PTN generation problem. One extreme condition is connecting all pairs of bus stops by direct shuttle service. Although it is extremely convenience for passengers, it requires an enormous cost to transportation companies.

3. METHOD

In this section, outline of our method with Multi Agent System is described. However, the process to generate initial set of line agent is replaced with newly developed process with community detection method in section3.2.

3.1 Multi Agent System

The developed MAS separates several components as follows.

- Generating initial set of line agent
- Route selection of passengers
- Evolution of line agent

Briefly speaking about original generator for initial line set in the first component, a growing network model [8] was modified [11]. However it produces many lines that route is different from each other. In addition, it is recognized that the initial line set affects to the transportation performance of obtained PTN and computing times[12]. The community detection algorithm in section 3.2 is used to generate initial set of line agent in this paper.

After generation of the initial set of line, evolution process of the MAS starts. In the process, above second and third components are executed alternately. Fig.2 illustrates the flow diagram of the process. # 2 in Fig.2 (Section 3.1.1) corresponds to the second component. # 3-6 in Fig.2 (Section 3.1.2-3.1.5) corresponds to the third component. Line agents without passenger are deleted in each evolution step. Thus the number of line agents declines eventually.

3.1.1 *Route Selection of Passenger*

In this paper, it is assumed that the user of PTN selects shortest path in time. It means minimizing the first term in Eq.1. This subsection describes the method to analyze the in-vehicle time, waiting time, transfer number for all OD pairs(Fig.2, # 2). The result of the analysis is utilized in the section 3.1.2.

To analyze the route selection of passengers, PTN is converted to the network in Fig.3 separating bus stop into physical world node and virtual node.

For instance, since the "line a" and "line b" share the bus stop 3, the figure shows two virtual bus stops, a3 and b3. There are three kind of link and arcs in the converted network. One is "Line Link" connecting virtual bus stops. Second is "Boarding Arc" from physical bus stops to virtual bus stop belonging to lines. Third is "Alighting Arc" from virtual bus stops to physical bus stops. The weight of the "Line Link" is in-vehicle time (Link Length/Moving Speed), "Boarding Arc" is waiting time (Headway/2 representing expectation value of waiting time) and "Alighting Arc" has no

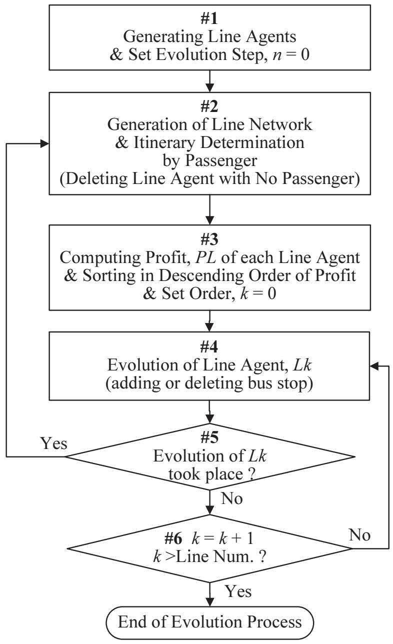

Figure 2: Flow Diagram

weight. Furthermore, to represent transfer cost, five minutes is added to the weight of boarding links. (System does not assign the five minutes to first riding.)

Since the weight of the link and arc in this network is time, shortest path algorithm like Dijkstra Method with heap sort algorithm [15] can immediately find out the shortest paths in travel time.

3.1.2 Evolution of Bus Line Agent

Evolution rule of line agent changes transit route and vehicle number. Using the result of the previous subsection, the line agent evolves in selfish to increase the profit defined by the following formula. To encourage the evolution of line agent with higher profit, the target agent is selected in descending order of the profit(# 3 in Fig.2).

$$P_{L_k} = R^n_{L_k} - w_2 B^n_{L_k} \tag{2}$$

where, n is evolution step, R_{L_k}, B_{L_k} are number of user and vehicle of line agent L_k respectively. w_2 is control parameter for the relationship between user number as benefit and vehicle number as cost. It is expected that small w_2 leads to an extension of its transit route to get users and large w_2 leads to a shrink of its transit route to reduce vehicle number.

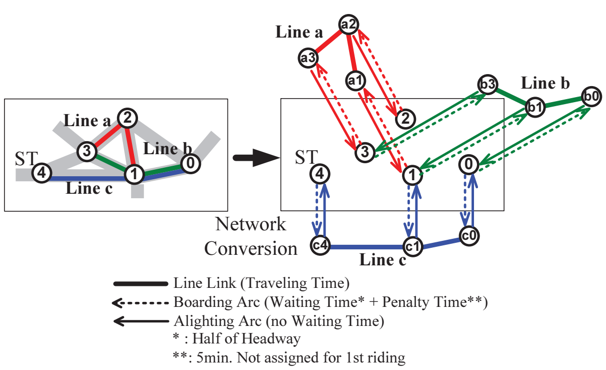

Figure 3: Network Conversion

Furthermore, user number, R_{L_k} and vehicle number, B_{L_k} is computed by the following equations.

$$R^n_{L_k} = \sum_{S_i \in L_k} d^n_{S_i, L_k} \tag{3}$$

$$B^n_{L_k} = \lceil \max(B^n_{min}, B^n_{opt}, 1) \rceil \tag{4}$$

$$B^n_{min} = \max_{S_i, S_{i+1} \in L_k} (d^n_{S_i, S_{i+1}}) Tr^n_{L_k} / C_B \tag{5}$$

$$B^n_{opt} = \sqrt{Tr^n_{L_k} R^n_{L_k} / (2w_1)} \tag{6}$$

where, $d_{i,j}$ is head-count moving from i to j that is obtained by user's route selection analyzed in the previous subsection. i, j stand for physical bus stops or virtual bus stops in lines. In case of that i is a physical bus stop and j is a virtual bus stop, it means head-count boarding the line of j at the bus stop i. Eq.5 is minimum vehicle number to satisfy the boarding demand and $\max_{S_i, S_{i+1} \in L_k}(d^n_{S_i, S_{i+1}})$ in the equation is maximum traffic volume between adjacent virtual bus stops, S_i, S_{i+1}, belonging to line agent L_k. Eq.6 is the vehicle number minimizing the evaluation value of Eq.1 if Eq.1 is applied only to the line, L_k. Eq.6 is derived from the fact that the evaluation value becomes minimum at the point where waiting time as user's cost is same to the vehicle number of operator's cost[4].

Next step is evolution strategy of target line agent (# 4 in Fig.2). The target line agent, L_k, considers all combinations of inclusion of one bus stop not belonging to the line, $S_j \notin L_k$, and exclusion of one bus stop belonging to the line, $S_i \in L_k$.

All combinations of target bus stop and operation(inclusion and exclusion) are evaluated by the procedure of following sections. For example, if line b in Fig.3 becomes target agent, it considers four patterns in Fig.4. (Exclusion of ST1 is omitted. Because shortest path between ST0 and ST3 runs through ST1.)

3.1.3 Inclusion of Bus Stop

In case of inclusion of bus stop not belonging to the target line agent, $S_j \notin L_k$, it considers insertion of the bus stop, into adjacent two bus stops, S_i,$S_{i+1} \in L_k$. (It is also considered that S_i or S_{i+1} is terminal bus stop.) If there are more than one insertion point, it selects the point with minimum increase of the line length. Eventually, the line agent expects the change of the profit, A_{S_j}, by following equation.

$$A_{S_j} = \Delta R_{L_k} - w_2 (B^{n+1}_{L_k} - B^n_{L_k}) \tag{7}$$

$$\Delta R_{L_k} = \sum_{S_i \in L_k, S_j \notin L_k} D^n_{S_j, S_i} \tag{8}$$

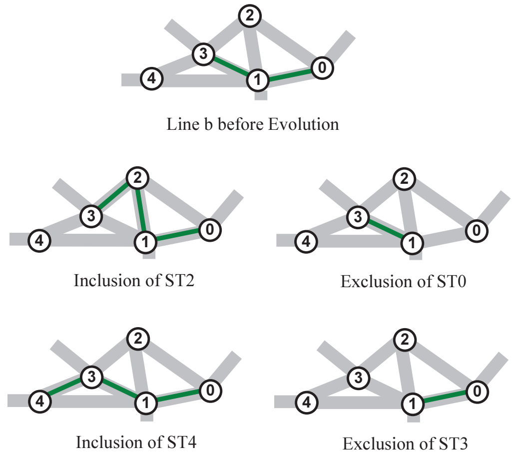

Figure 4: Line Evolution (Left Column is Inclusion, Right Column is Exclusion of one bus stop)

where, D_{S_j,S_i} is head-count whose origin bus stop is $S_j \notin L_k$ and destination bus stop is $S_i \in L_k$ (given by OD matrix). However, to estimate pure increase of head-count using L_k, demand already using the line L_k isn't counted. The super script $n+1$ of B_{L_k} in Eq.7 means estimated vehicle number after evolution and it is computed by following equations.

$$B_{L_k}^{n+1} = \max(B_{min}^n, B_{opt}^{n+1}, 1) \tag{9}$$

$$B_{opt}^{n+1} = \sqrt{Tr_{L_k}^{n+1}(R_{L_k}^n + \Delta R_{L_k})/(2w_1)} \tag{10}$$

where, $Tr_{L_k}^{n+1}$ is round trip time of vehicle assigned for the target line after inclusion of the bus stop.

3.1.4 Exclusion of Bus Stop

In case of exclusion of a bus stop belonging to the target line agent $S_i \in L_k$, its profit A_{S_i} declines, assuming that the number of passenger utilizing the target line L_k at bus stop S_i becomes zero.

$$A_{S_i} = \Delta R_{L_k} - w_2(B_{L_k}^{n+1} - B_{L_k}^n) \tag{11}$$

$$\Delta R_{L_k} = -d_{S_i,L_k}^n \tag{12}$$

The vehicle number $B_{L_k}^{n+1}$ in Eq.11 is estimation value due to the exclusion of the bus stop $S_i \in L_k$ and it is calculated by Eq.9 and Eq.10 with the round trip time $Tr_{L_k}^{n+1}$ after exclusion of the bus stop.

However, the change of the profit A_{S_i} or A_{S_j} isn't computed if the following condition is true.

* Inclusion or exclusion of bus stop that violate the whistle-stop tour as prerequisite
* Exclusion of bus stop resulting in isolation of the bus stop from PTN
* Re-inclusion of a bus stop excluded by same line agent

3.1.5 Selection of Evolution Pattern

The target line agent selects the combination of operation (inclusion and exclusion) and bus stop with maximum change of profit, π defined by the following equation. It means greedy strategy.

$$\pi = \max_{S_i,S_j}(A_{S_i}, A_{S_j}) \tag{13}$$

However, if $\pi < 0$ is true, the evolution of the target line agent does not take place (arrow from # 5 to "No" in Fig.2). The target line agent is changed to the line agent with next highest profit, L_{k+1} (arrow from # 6 to "No" in Fig.2).

If evolution of the target line agent took place, process moves to the user's route selection in the section 3.1.1. (arrow from # 5 to "Yes" in Fig.2). Eventually evolution process terminates if all line agents meet with the condition, $\pi < 0$ (arrow from # 6 to "Yes" in Fig.2).

3.2 Community Detection

A number of community detection methods are proposed and they are mainly applied to social networks. Some papers applying the method to transport networks has begun to appear[9], [10]. In this paper, it is indicated that community detection methods have potential to be useful application to find out effective routes on public transport network (PTN). Because, it can be imagined intuitively that node collection connected by many links (i.e. community) corresponds to nodes of an effective line. Trying some community detection algorithms, following procedure is employed.

Overlapping community detection algorithm was proposed in a paper[2]. Since several lines stop at one station, overlap is an imperative element for generating PTN. However, original model deals with adjacency matrix A. It means that element A_{ij} is 1 if node i and j is connected by a link and it is 0 if not connected. Considering application for transport network, distance and demand are crucial. Thus, the adjacency matrix A is replaced with weight matrix W_{ij} that is function of distance and demand.

$$W_{ij} = \frac{D_{ij}^{\alpha}}{L_{ij}^{\beta}} \tag{14}$$

where, α, β is elasticity parameter for demand D_{ij} and distance L_{ij} respectively. To obtain rational communities, following likelihood, P is maximized.

$$\log P(G|\theta) = \sum_{ijz}\{q_{ij}W_{ij}\log\frac{\theta_{iz}\theta_{jz}}{q_{ij}(z)} - \theta_{iz}\theta_{jz}\} \tag{15}$$

where, z is community ID, θ_{iz} is propensity of node i to have links of community z. (In this method, link is also assigned to communities.) $\theta_{iz}\theta_{jz}$ means expected number of links of community z that lie between node i and j. q is parameter satisfying, $q_{ij}(z) > 0$, $\sum_z q_{ij}(z) = 1$ and is probability that link between i and j belongs to community z.

Maximizing process is as follows. The number of community should be given before the maximizing process (This is one of drawbacks of the method.). At the beginning of the process, all links are assigned to randomly selected community. Furthermore, θ and q are updated repeatedly with following two equations.

$$\theta_{iz}^{(k)} = \frac{\sum_j W_{ij} q_{ij}(z)^{(k)}}{\sqrt{\sum_{ij} W_{ij} q_{ij}(z)^{(k)}}} \tag{16}$$

$$q_{ij}^{(k+1)} = \frac{\theta_{iz}^{(k)} \theta_{jz}^{(k)}}{\sum_z \theta_{iz}^{(k)} \theta_{jz}^{(k)}} \tag{17}$$

where, k stands for repeat number. Although, the likelihood increases monotonically during above process, the converged solution is not global optimum solution but a local optimum solution. Thus, a number of iterations starting with random assignment are required to avoid getting stuck in a local optimum.

In the original paper[2], more sophisticated implementation to save computer resources is proposed.

4. ANALYSIS

In this section, the first subsection shows performance of the community detection algorithm for a simple circular network. The second subsection explains a benchmark problem. The last subsection demonstrates an application of the MAS with community detection algorithm to the benchmark problem.

4.1 Analysis for Community Detection

The community detection algorithm in section 3.2 is applied to a simple street network in the Euclidean space, which has eight nodes(Fig5). The street network is assumed complete graph connecting any combination of two nodes by a link.

The number of community is set to 2. The elasticity parameters are $\alpha = 0$, $\beta = 1, 3$. It implies only distance affect to the result. Fig.5 shows result of community detection. In this figure, Nodes are represented by circle chart that means ratio of community to which nodes belong. The ratio is calculated based on the variable, θ_{iz}. As expected, the two communities have line symmetry. In case of $\beta = 3$, the communities are divided more clearly than the result of $\beta = 1$.

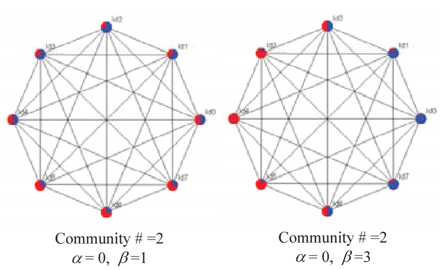

Figure 5: Result of Community Detection

4.2 Benchmark Problem

The method in the previous section 3.1 with initial line set generated by community detection method is applied to a benchmark problem [13]. Fig.6 illustrates street network. The number in node is ID and the number along side with the link is in-vehicle time in minutes. Table 1 shows OD demand matrix for one day that almost every pair of two bus stops have demand. The seating capacity of vehicle is set to 50 persons. Cost for transferring is set to 5 minutes/(person x number of transferring).

Table 1: OD Demand Matrix of Benchmark Problem

ST	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	0	400	200	60	80	150	75	75	30	160	30	25	35	0
1	400	0	50	120	20	180	90	90	15	130	20	10	10	5
2	200	50	0	40	60	180	90	90	15	45	20	10	10	5
3	60	120	40	0	50	100	50	50	15	240	40	25	10	5
4	80	20	60	50	0	50	25	25	10	120	20	15	5	0
5	150	180	180	100	50	0	100	100	30	880	60	15	15	10
6	75	90	90	50	25	100	0	50	15	440	35	10	10	5
7	75	90	90	50	25	100	50	0	15	440	35	10	10	5
8	30	15	15	15	10	30	15	15	0	140	20	5	0	0
9	160	130	45	240	120	880	440	440	140	0	600	250	500	200
10	30	20	20	40	20	60	35	35	20	600	0	75	95	15
11	25	10	10	25	15	15	10	10	5	250	75	0	70	0
12	35	10	10	10	5	15	10	10	0	500	95	70	0	45
13	0	5	5	5	0	10	5	5	0	200	15	0	45	0

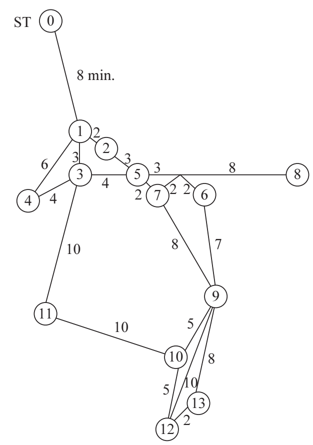

Figure 6: Infrastructure Network of Benchmark Problem

4.3 Result of Benchmark Problem

Fig.7 and Table2 show result of community detection method. The elasticity parameters are $\alpha = 1$ and $\beta = 1$. Thus, larger demand and shorter distance forms stronger connection. Since the line number of the best solution in Table 4 is six, number of community is set to the identical number, six. Result with twelve (twice the number of six) communities is also shown in Table4 as supplemental information. However, following result and discussion describes on the result of six communities unless otherwise stated. Because, smaller number of initial line agent increases the potential for saving computational resources.

Table2 is rate of community to which node assigned. Selecting upper 40% elements from the table, six routes in Table 3 are obtained. Ordering the nodes in one community to obtain line route relied on two-opt algorithm [3] for travel salesman problem. After deleting one link with maximum distance (In this paper, route is not circular like travel salesman problem.), the route with minimum distance was found by repeating swap of two nodes. Using the six routes as route of initial line agent, the evolution process of MAS was executed.

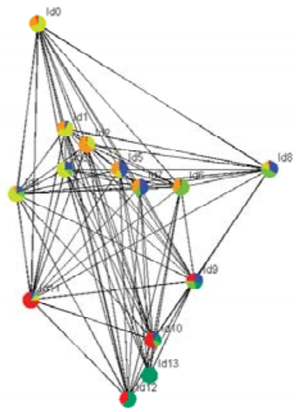

Figure 7: Result of Community Analysis

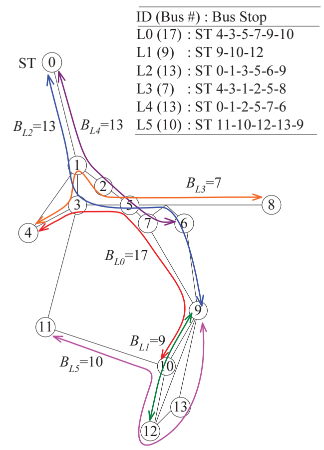

Figure 8: PTN by This Method

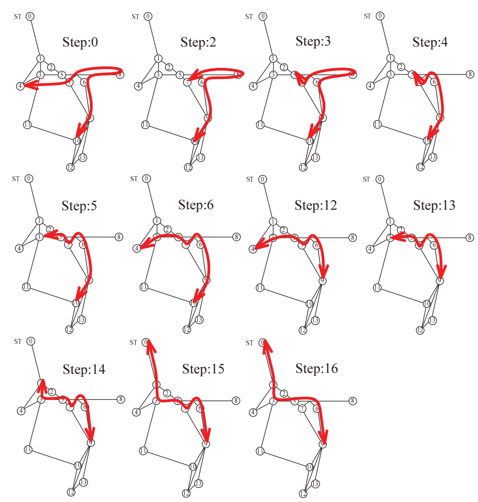

Figure 9: Evolution of Line Agent

Table 2: Result of Community Detection for Benchmark Problem

ST/com	com0	com1	com2	com3	com4	com5
ST0	0.00	0.00	0.04	0.63	0.29	0.04
ST1	0.07	0.00	0.03	0.60	0.30	0.00
ST2	0.00	0.01	0.02	0.31	0.65	0.01
ST3	0.25	0.01	0.13	0.61	0.00	0.00
ST4	0.16	0.00	0.15	0.61	0.08	0.00
ST5	0.43	0.02	0.00	0.17	0.37	0.00
ST6	0.00	0.02	0.63	0.00	0.31	0.03
ST7	0.48	0.02	0.17	0.00	0.34	0.00
ST8	0.35	0.00	0.42	0.16	0.06	0.02
ST9	0.28	0.20	0.24	0.03	0.00	0.25
ST10	0.10	0.20	0.15	0.00	0.00	0.55
ST11	0.08	0.00	0.06	0.12	0.00	0.74
ST12	0.00	0.62	0.00	0.01	0.00	0.37
ST13	0.00	1.00	0.00	0.00	0.00	0.00

The results of previous studies and this method are summarized in Table 4. Fig.8 shows PTN obtained after evolution process by this method. Fig.9 shows evolution process of line agent 2 (L2) in Fig.8. Fig.10 is comparison of the evolution history of total travel time and vehicle number between best solution and result of this method. The difference of original method that output the best solution and this method is limited to the process generating initial line agent. In this method, the process was replaced with community detection method described above.

5. DISCUSSION

Table 4 shows that the result of this method in case of 6 communities is that total travel time is 3,406 hrs and vehicle number is 69. This result is worse than one of the best solutions (3,291 hrs and 64 vehicles) obtained by our original method in terms of both total travel time and number of vehicle. Comparing with the other results in Table 4, however, this method with 6 communities outputs PTN with medium quality. (Out of the 11 results, the rank of total travel time is 7th and rank of vehicle number is 4th) Furthermore, the best solution by the original method has more than 30 initial line agents and its final evolution step is 55. On the other hand, this method utilizes only six initial line agents detected by community analysis and final evolution step is 18. Fig.10 shows comparison of the history of total travel time and vehicle number in the evolution process between original method and this method. Not only evolution steps but also variation of the total travel time and vehicle number of this method is smaller than that of original method. It implies that the routes found by community detection are comparatively high quality and it leads to fewer evolution steps. This is an advantage of this method. Because computation time will be saved if target network becomes large scale. Fig.11 shows relationship between computation

Table 3: Route obtained by community detection

Route:	Nodes					
Route0:	ST4	ST3	ST5	ST7	ST9	ST8	
Route1:	ST13	ST12	ST10	ST9			
Route2:	ST10	ST9	ST6	ST8	ST7	ST4	
Route3:	ST8	ST5	ST2	ST0	ST1	ST3	ST4
Route4:	ST0	ST1	ST2	ST5	ST7	ST6	
Route5:	ST11	ST10	ST12	ST9			

Table 4: Comparison of Results for Benchmark Problem

	Baaj[1]			Mandl[13]	Shih[16]	Zhao[17]		Majima[12]		This Method	
										Com.#=6	Com.#=12
Directly(%)	78.6	80.0	81.0	69.9	87.7	99.1	99.0	94.6	88.3	87.2	92.7
Transfer1(%)	21.4	20.0	19.0	29.9	12.3	0.90	1.0	5.4	11.6	11.8	7.0
Transfer2(%)	0	0	0	0.13	0	0	0	0	0.1	1.0	0.3
Total(hr)	3428	3511	3714	3651	3401	3272	3285	3244	3291	3406	3301
In-Vehicle(hr)	2801	2818	3006	2957	N.A.	N.A.	N.A.	2662	2661	2745	2677
Waiting(hr)	349	432	462	302	N.A.	N.A.	N.A.	512	478	483	525
Transfer(hr)	278	260	247	392	159	11.7	13.4	70	152	178	99
Line Num.	N.A.	N.A.	N.A.	4	8	4	6	6	6	6	5
Vehicle Num.	89.3	76.9	82.2	99.3	68	82	77	72	64	69	64

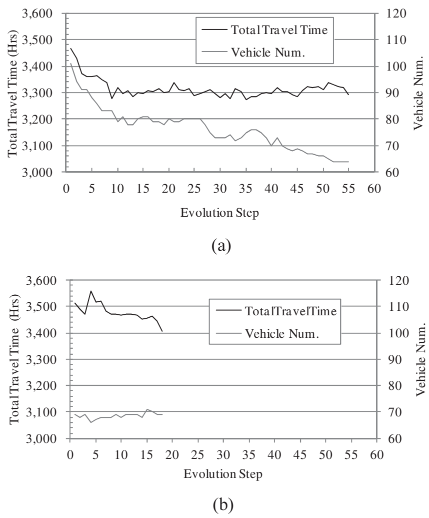

Figure 10: History of Total Travel Time and Vehicle Number (a) Original Method (b) This Method

time of our original method and network size. It reveals that original method needs computation time proportional to $n^3 \log_2 n$ (n is number of node).

Whereas in case of 12 communities in Table4, total travel time is 3,301 hrs and vehicle number is 64. Although this result is better than that of 6 communities, total travel time is worse than one of the best solutions (3,244 hrs and 72 vehicles). As described above, larger number of initial line agent has potential to output better solutions. However, it also has potential to need larger number of evolution steps (59 steps in this case). In addition, too many number of communities blurs the bound of community and at this time we don't have strategy to find out appropriate number of community ahead of analysis. This is disadvantage of the community detection method.

As is shown in Fig.9, most of the 18 steps of this method with 6 communities are caused by evolution of the line agent L2 in Fig.8, whereas the change of the other lines is small. (It can be recognized by comparing Table 3 and Fig.8.) The behavior in Fig.9 looks like a foraging activity of living creatures in nature. Generally speaking, the line agents have a tendency to extend their route if there are large demand and have a tendency to shrink their route if there are not enough

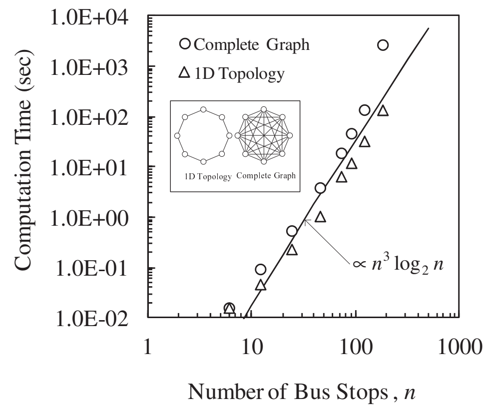

Figure 11: Relationship between Network Size and Computation Time. (All OD pairs have demand.)

demand.

6. CONCLUSION

The problem of generating public transport network (PTN) is a hard problem. Especially the procedure finding proper routes meets difficulty due to large number of combination. In this paper, community detection algorithm is applied to generate initial line routes. The final result obtained by community analysis does not reach to the best solution for the benchmark problem. However it is found that the method outputs PTN with moderate quality and it has advantage to reduce number of candidate routes for PTN.

There are some meta-heuristic approaches for the PTN generation problem, such as GA[5], [14] and SA[6], [17]. and their optimization process also needs set of candidate routes. It is envisaged that sophisticated route generated by the community detection will help another methods other than our MAS.

The Great East Japan Earthquake on March 11th 2011 struck eastern coastal area of the Japanese main island. Many commuters around Tokyo met with difficulty to return to their homes due to the shut down of railway transportation system (It is called "stranded commuter problem"). However, if massive earthquake directly strike the areas around Tokyo, there is no transportation system for a long while. Our final purpose is to provide a PTN immediately as an alternative transportation system for railways.

Under such situation, we believe that PTN generated with the method in this paper will become useful, even though it is limited to simple information (route and headway of each line).

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8. REFERENCES

[1] M. H. Baaj and H. S. Mahmassani. An ai-based approach for trtansit route system planning and design. Journal of Advanced Transportation, Vol.25, No.2, pp.187-210, 1991.

[2] B. Ball, B. Karrer, and M. E. J. Newman. An efficient and principled method for detecting communities in networks. Phys. Rev. E 84, 036103, 2011.

[3] D. P. Bertsekas. Network Optimization: Continuous and Discrete Models. Athena Scientific, 1st edition, 1998.

[4] B. Byrne. Public transportation line positions and headways for minimum user and system cost in a radial case. Transportation Research, Vol.9, pp.97-102, 1975.

[5] P. Charkroborty and T. Dwivedi. Optimal route network design for transit systems using genetic algorithms. Engineering Optimization, Vol.34 No.1, pp.83-100, 2002.

[6] W. Fan and R. B. Machemehl. Using a simulated annealing algorithm to solve the transit route network design problem. Journal of Transportation Engineering, Vol.132, No.2, pp.122-132, 2006.

[7] R. Z. Farahani, E. Miandoabchi, W. Szeto, and H. Rashidi. A review of urban transportation network design problems. European Journal of Operational Research, Vol.229, pp.281-302, 2013.

[8] M. T. Gastner and M. E. J. Newman. Shape and efficiency in spatial distribution networks. Journal of Statistical Mechanics, P01015, 2006.

[9] P. Kaluza, A. Kölzsch, M. T. Gastner, and B. Blasius. The complex network of global cargo ship movements. Journal of the Royal Society Interface, Vol.7, No.48, pp.1093-1103, 2010.

[10] V. D. Leo, G. Santoboni, F. Cerina, M. Mureddu, L. Secchi, and A. Chessa. Community core detection in transportation networks. Phys. Rev. E 88, 042810, 2013.

[11] T. Majima, K. Takadama, D. Watanabe, and M. Katuhara. Network evolution model for route design of public transport system. Workshop on Emergent Intelligence on Networked Agents (WEIN'07), pp.57-69, 2007.

[12] T. Majima, K. Takadama, D. Watanabe, and M. Katuhara. Network evolution, modifying model for public transit network. Transactions on Mathematical Modeling and its Applications, Vol.2, No.2, pp.92-102 (in Japanese), 2009.

[13] C. Mandl. Evaluation and optimization of urban public transportation networks. Presented at the 3rd European Congress on Operation Research Amsterdam, Netherlands, 1979.

[14] S. Pattnaik, S. Mohan, and V. Tom. Urban bus transit route network design using genetic algorithm. Journal of transportation engineering, Vol.124, No.4, pp.368-375, 1998.

[15] R. Sedgewick. Algorithms in C Part 5 Graph Algorithms. Addison-Wesley, 3rd edition, 2002.

[16] M.-C. Shih and H. Mahmassani. A design methodology for bus transit networks with coordinated operations. SWUTC/94/60016-1, Center for Transportation, Univ. of Texas at Austin, 1994.

[17] F. Zhao and X. Zeng. Optimization of user and operator cost for large-scale transit network. Journal of Transportation Engineering, Vol.133, No.4, pp.240-251, 2007.