

Optimization Urban Freight Transportation Network by Using Genetic Algorithm

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Abstract :The development of road network to optimize cost of urban freight transportation is very difficult to be conducted. Therefore, implementable alternative for optimizing the cost employs a selection metode to obtain a set of route as a path for freight. The route selection is a combinatoric optimization problem. The problem is here depicted in an activity to identify and select a group of actions that can be recommended from a number of actions that can be conducted. Vehicle behavior in selecting its path is carefully considered in accordance with its characteristics and traffic flow. This research was conducted in a framework of bilevel and mathematics model developed in the formulation of route election. The combination of route selected is optimized by using the procedure of Genetic Algorithm. The model was verified by applying it on a hypothetical network. The result is a model with Genetic Algorithm approach that can provide an optimal path of urban freight transport network.

Keywords : route choice, urban freight transport network, multiuser class, bi-level programming, Genetic Algorithm

1. INTRODUCTION

In every urban region in the world, in general, there are a path of freight for transporting several types of goods. In Indonesia it is known as a path of freight transport. Meanwhile, for a group of public goods transported using heavy vehicles such as truck with 2 axles up to trailers that have a final destination at region in a city, their movements have to be frequently limited by specifying a route with certain criterion that they can or will never pass. The Freight path selection is based on the contribution of traffic jam generated by this vehicle type, and they have to make a competition with other users on a limited system of road transport network infrastructure in the urban areas in terms of finding the optimal route for their transportation. Thus, the path selection for freight transport network is started from a route choice for finding the best one.

Castro *et al.* (2009) have done an optimization of freight transport network by conducting a restriction mechanism for heavy vehicle of goods entering an urban area and trying to propose a set of route (ring road) as a set of path for freight transport. The proposed method is applicable at urban areas because it can reduce congestion and NOx and PM emission per unit time, along the road length.

The main purpose of the selection of freight route is for efficiency (Taniguchi, 2007). Because of the limited road infrastructure and the difficulty in its development in the urban areas, forces freight carrier to compete with other users in selecting their route for finding the

optimal travel cost. Therefore, for optimal expense of transport, the planner for freight transport network should make a planning of route choice for the best path of their fleet.

In the context of this case, the route choice is included in a combinatoric optimization problem. The problem is here depicted in an activity to identify and select a group of actions that can be recommended from a number of actions that can probably be conducted. In this case, vehicle behavior in selecting its path is carefully considered in accordance with its characteristics and traffic flow. For finding the best solution that considered freight operator and the other users, this research was conducted in two-level programming framework and mathematics model developed in the formulation of route choice model. The combination of the route would be generated on the phase of scenario development by using meta heuristic procedure, i.e. Genetic Algorithm.

2. LITERATURE REVIEW

Empirical studies on techniques trade off (open and closed system of roads) I have rarely encountered, one of the research is a study conducted by Tamin in 2012 (unpublished), namely the closure of toll roads in Jakarta for truck. The method used is a full combination, which tried several scenarios road closures. During its development, in 2013, Taniguchi et al, try doing the same thing in Japan.

The concept of bi-level programming for decision making has expanded since a long time ago and this concept can be applied in the course of stipulating a path on freight transport network. For urban areas, Taniguchi and Thomson (2003) have developed a concept of city logistics in the framework of bi-level. Nevertheless, the behavior of freight carrier have not been yet influenced by traffic behavior of other user.

Bi-level programming is a two level decision making of a decision maker's behavior in specifying the optimum path of freight that consists of lower level and upper level. At the lower level, the traffic flow behavior of freight carrier and other user is considered as an effort to model the reality in a modeling framework, whereas the upper level represents the decision maker's behavior having an objective with a certain method of analysis.

Taniguchi *et al.*(2000) have developed a vehicle routing problem for city logistic. Their proposed method for route choice of freight vehicle depends on total link cost of freight by considering other user's behavior on the network. The other user's behavioral was assumed constant. GA procedure was used to solve the problem. On this case, they set the problem as a single objective optimization problem and considering only freight transport cost. Therefore, the result finding just only accommodate only one user, here was total cost of freight vehicle. The performance of GA for this problem was so powerfull. It could found the solution just only in a few seconds. On their other research, Taniguchi *et al.* (2007) proposed a method to find solution of vehicle route in term to optimize two contrary objectives, here are minimize cost and NO_x emssion. By using GA, they found that the result was not always the best for all objective. It was could be explained as follows: this case was a pareto problem. It was mean, there was no one solution would dominate the other solution. So, the conclusion of Taniguchi research fullfiled pareto condition, and the result should be the win win solution among the objective (non dominated solution). Other researchers (Frazilla *et al.*, 2005; Yamada *et al.*, 2010; Taniguchi *et al.*, 2007) have developed a route choice for freight that is influenced by dynamic traffic flows caused by other user's behavior. Further, for the lower level, Frazilla *et al.*(2010) have considered multimodal and multiuser class for their network model. All of those reseachers have developed their model in the bi-level programming framework.

At the upper level, the behavior of the policy maker is represented by a systematic method for designing freight transport network with a certain objective. Related to the model

developed at the upper level, in the year 2009, Taniguchi *et al.* repairs the objective function in the election of the vehicle route by considering their impact on air pollution, which is NO_x. And the principle of the bi level is implemented in the concept of multi agent, whereas the method for the best route election has been developed by Genetic Algorithm (GA). The improvement of GA has been developed by Frazilla (2005) and Yamada *et al.* (2010).

There are three types of method for solving combinatory optimization problem for bi-level programming: a strict, approximate, and metaheuristic method. In the previous decade, some metaheuristic procedures have been developed and applied in the environment of soft computing. The role of the technique is to solve a complicated and difficult mathematics programming problem, which entangles a difficult network problem (NP-hard Problem). This technique cannot ensure an exact result of optimal solution, but it can provide a reasonable and practical result. Therefore, this method is usually applied for combinatoric optimization problem in which an exact result of optimal solution is difficult to determine.

Ribeiro and Hansen (2001), Michalewicz and Fogel (2002), Glover and Kochenberger (2003), Herz and Widmer (2003), and Resende and Pinho de Sousa (2004) have introduced a good elementary concept of metaheuristic. Generally, genetic algorithms (e.g.,: Holland, 1975; Goldberg, 1989; Davis, 1991; Reeves, 1997), taboo search (e.g.,: Glover and McMillan, 1986; Glover and Laguna, 1997), simulated annealing (e.g., : Kirkpatrick *et al.*, 1983; Aarts and Korst, 1989), and ant colony optimization (e.g.,: Dorigo *et al.* 1999; Dorigo and Stutzle, 2004) are typical solution techniques in metaheuristic. From the various metaheuristic techniques for combinatoric optimization above, genetic algorithm is commonly used and developed in so many variants because of its reliability in solving problems. Nevertheless, there is a possibility of other metaheuristic solution technique that can provide a better result.

Genetic Algorithm is a metaheuristic method introduced by Holland (1979) which relied on natural selection mechanism and genetics. A possible solution built is an individual known as chromosome. Every position in chromosome is known as gene and gene values are recognized as allelic values. The allelic value most commonly is a binary value from {0,1}. A number of individuals a probably selected to become a solution form a population. The selection of the best solution began from random chromosome population that represents possible solution for the problems. The population of the chromosome will be evaluated by using a definite fitness function and a new set of population is generated by a genetic operator. Every generation will be selected by using a local search, and to evaluate the rest capacity of each population of chromosome, a fitness function and a simple operator (selection, reproduction and mutation) are used as a mean to generate a new set from the artificial population.

Some of GA applications in the optimization problem has been discussed by Golgberg (1989). In the transportation area, GA has also been widely applied. Cantarella and Vitetta (1994) used GA in a multi level programming for network design and urban parking problem. At a broader level, a new road network configuration is evaluated by genetics procedure. Besides the traffic assignment procedure, at the nucleus level, setting of traffic signal and assignment of flow on a link are explained by an iterative method. Setting of traffic signal, delay at the road network and temporary flow are cyclically calculated up to two successive patterns of traffic flow controlled in a certain tolerance.

Xiong and Schneider (1993) introduced a repair version of GA, The Cumulative Genetic Algorithm (CGA) and its application for designing a transportation network. At CGA, all population members which have a high value of fitness are preserved and together used with new population members as an input to reproduce. This matter has been also combined with an artificial neural network to provide a set of individual other than the previous generation (parent). Other hybrids of GA are proposed by Kwan and Wren (1994) that are applied for the

problem of bus driver scheduling. They unite GA, a rule that relied on estimation of driver duty and an integer programming.

GA is exploited to produce the best population and it is followed by integer programming to develop optimal driver scheduling. Yamada *et al.* (1999) use GA approach to solve the problem of designing size and location of optimal logistics terminal . To develop the algorithm performance, the high-class (elites) operator also participates. This Operator preserves the best individual (e.g.: chromosome whose function fitness has a high value) in a population to be used at the next generation. The next model development of GA involves a multi objective analysis, known as Vector Evaluation Genetic Algorithm, VEGA (Frazilla, 2005).

3. MODELLING

3.1 Modeling Framework

Generally, the framework for modeling the optimization of freight transport network in this paper is described as seen in the figure below:

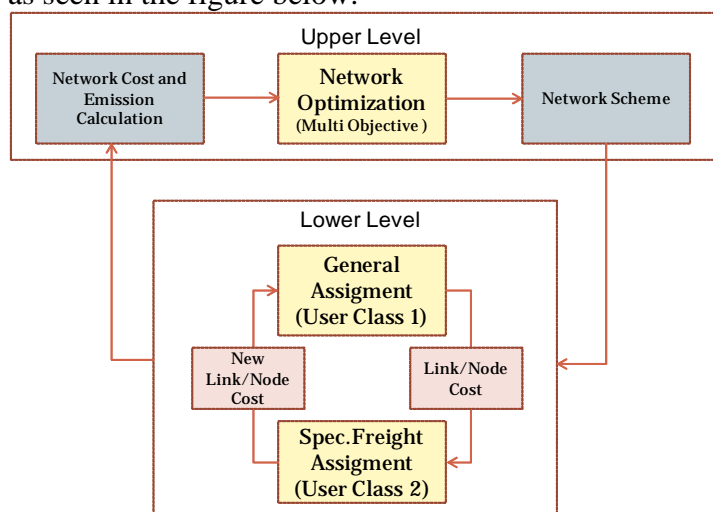


Figure 1 The Framework of Urban Freight Transportation Network Modeling

The picture above depicts a modeling framework for designing an urban freight transportation network in this paper. The framework above is a bi-level programming, where the problem at the upper level represents the administrator’s behavior (transport planner), whereas the behavior of freight carrier and other users are depicted at the lower level. The minimal of network expense and NOx emission are the objective to be reached. Those objectives are integrated in a solution technique proposed at the upper level.

3.2 Lower Level Problem

3.2.1 Transport Network Representation

Road network is generally represented as an origin and destination node as described on Figure 2. Figure 2 depicts a road network with two road links (road link I and II). These links connect a pair of nodes (node 3 and 4) that can become a choice of route from the origin zone

1 to the destination zone 2. The road is conditioned to be able to be passed by vehicles, either vehicle for freight or for passenger. The model of the link is represented by exploded link 1,3,5 at road link I and exploded link 2,4,6 at road link II alternately. This network representation is defined as an abstract network model $G(N,A)$, where N is a set of nodes and A is a set of link.

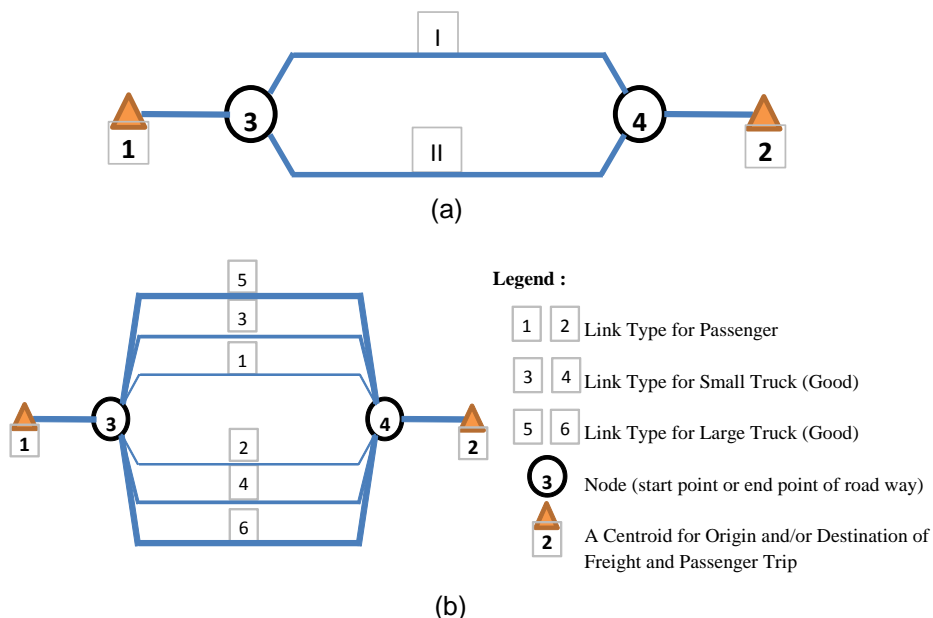


Figure 2 Representation of Urban Road Transportation Network

Node 3 and 4 are the examples of the node intersection. This research is conducted for urban design, so delay at an intersection becomes a very crucial matter and must be considered more comprehensively. For that reason, the representation of the traffic movement at an intersection is shown on the following picture (see Figure 3). The flow characteristic and the junction capacities would be considered for estimating the time delay.

Using this representation, the set of links A is composed of road links (A_j), turn left link of signalize (A_{ski}), through link of signalize (A_{sl}) and turn right link of signalize (A_{ska}), turn left link of priority (A_{pki}), through link of priority (A_{pl}) and turn right link of priority (A_{pka}) and centroid connectors (A_c), such that $A = A_j \cup A_{ski} \cup A_{sl} \cup A_{ska} \cup A_{pki} \cup A_{pl} \cup A_{pka} \cup A_c$.

Intersection is categorized into 2 types based on its type of operation control: priority and signal. Delay time on each approach at an intersection is counted comprehensively using a method mentioned in the Indonesian Highway Capacity Manual, 1997.

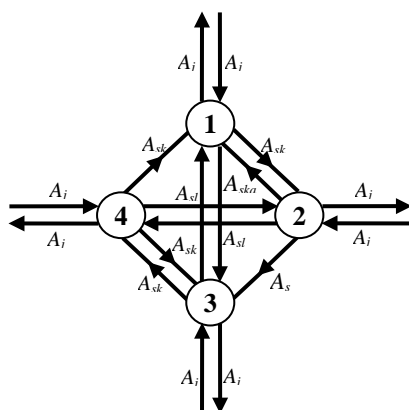


Figure 3 The Representation of Traffic Movement at a Junction

3.2.2 Link Cost Function

Link cost is a constraint for a vehicle to pass through on a link. The expense at a link a for user type i expressed as a generalized cost constructed from tariff component and travel time expense (Yamada *et al.* 2010), as shown by equation (1). The component of time expense is the multiplication result of delay time and time value for every user type.

$$c_a(x_a^i) = \rho_a^i + \alpha^i d_a^i(x_a^i) \quad (1)$$

where ,

- ρ_a^i : tariff of user type i on link a (Rp)
- α^i : time value for user type i (Rp/hour)
- $d_a^i(x_a^i)$: delay time of user type i on link a (hour)

The tariff component is a fixed value and does not depend on traffic volume, whereas the component of time expense, especially delay time, is a function of traffic volume and differs according to the link type . In this case, the link type is differentiated into the link representing a road and those representing the movement at an intersection. Furthermore, for traffic assignment on transport modeling, the two link types will be differentiated according to the user type. To avoid the complexity or the non-singularity solution, polynomial estimation (Crainic *et al.* 1990) is used for all link types as depicted by hereunder equation :

$$d_a^i(x_a^T) = t_0 \left(1 + \phi_1 x_a^T + \phi_2 \left(\frac{x_a^T}{r_a^T} \right)^\gamma \right) \quad (2)$$

where :

- x_a^T : total flow on link a (pcu/hour)
- r_a^T : total capacity on link a (pcu/hour)
- ϕ_1, ϕ_2, γ : calibrated parameter
- dai(xaT) : delay time of user type i on link a

3.2.3 Solution Technique

User equilibrium (UE) approach that relied on the principle of Wardrop user optimal is used on the traffic assignment model. In the case where Jacobian matrix from the link cost function is symmetric, the flow of UE can be taken as the solution to the problem of minimizing the convex cost. In this research, freight vehicles and other user are considered as multiclass users, with mode selection and route choice conducted simultaneously. Then, the traffic assignment is conducted by converting the multimodal network as a unimodal abstract network. Thus, the UE problem can be solved with a non-separable and Jacobian asymmetric of cost function matrix among of user type. The representation of traffic assignment model as mentioned above can be expressed as a variational inequality (Dafermos,1980 in Nagurney,2000; Frazila, 2005), with a formulation as follows :

$$\text{find } x_a^{i*} \in K , \quad (3)$$

So that :

$$\sum_{i=1}^P \sum_{a \in A} c_a^i(x) x(x_a^i - x_a^{i*}) \geq 0 \quad \forall \tilde{x} \in K, \quad (4)$$

where x_a^{i*} is UE flow on link a for user type i , and \tilde{x} is a column vector of p dimension with a component of $\{x_a^1, \dots, x_a^p\}$. K is defined as $K \equiv \{ \tilde{x} \mid \text{satisfying link flow and non negative conservative flow. } c_a^i(.) \text{ is generalize cost on link } a \text{ for user type } i, \text{ and } A \text{ is a set of links on road transportation network.}$

Marginal costs of freight transportation that uses a certain modal are assumed inelastic with other modes, hence multimodal assignment problem can be done as singlemodal assignment with various types of link. And because there are more than one user assigned, this case is considered as multiclass UE assignment problem with non-separable and asymmetric cost function. The method widely used to solve a case like this is diagonalization. This technique works with assumption when conducting a renewal flow from user type 1 at the next iteration; the flow from the other user type is assumed fixed. This technique is conducted simultaneously till there is no significant change at the produced flows. To reach a convergence condition, link cost is affected only by that flow.

3.3 Upper Level Problem

3.3.1 Objective Function

The objective function at the upper level problem is based on the difference of the total generalized cost of existing conditions with a total generalized cost after implementation of the action (opening and closing of roads). This is a simplification of the economic feasibility of the economy indicates the effectiveness of an action. This parameter (formulated as follows) can analyze the relative improvement (compared to the initial conditions) of a combination of such action.

$$Max f(y) = \sum_{i=F} \left[\sum_{a \in A_1 \cup A_2} x_{0a}^{i*} c_a^i(x_{0a}^{i*}) - \left(\sum_{a \in A_1} x_a^{i*} c_a^i(x_a^{i*}) + \sum_{a \in A_2} x_a^{i*} c_a^i(x_a^{i*}, y_a) \right) \right] \quad (5)$$

Where,

x_a^{i*} : flow of user type i on link a , (veh/hour) that is a solution of UE problems with the implementation of a combination of action.

$c_a^i(x_a^{i*}, y_a)$: generalised cost for link a according to the type of users that depend on the equilibrium flow and whether such action are implemented or not (indicator implementation of action, y_a) (Rp)

A_1 : set of existing link that are not modified

A_2 : set of existing links that allow an action can be implemented.

3.3.2 Solution Technique

As described above, the problems at the upper level are those of combinatoric and of the solution technique for optimization. The solution proposed is heuristic method of genetics algorithm. The applied method of genetics algorithm is very simple. It is not any more complex than duplicating the chromosome or exchanging some of the chromosomes of the individuals. On the other hand, the simplification of the operation and the influence of strength are two genetics algorithm characteristics that make this method very attractive. The elementary operator most commonly used in GA are reproduction, crossover and mutation.

The role of GA procedure in this model is very significant. In upper level, GA procedure with its operator (i.e crossover and mutation) produce combination of action from

possible alternative of action. GA would make 255 or (2^8-1) of combination of action. 8 is a number of possible alternative of action. Each combination of action will be tested by running traffic assignment which is called by GA procedure. The result from traffic assignment simulation i.e. traffic volume and link cost from each of link in the hypothetical network would be take over by GA procedure to calculate objective function of each combination. GA then calculate the fitness value for the first generation. If the fitness value of each individu in a generation have not reached convergence level, GA procedure would generate a new generation until the maximum number of generation set in advance is fullfilled. Here, reproduction and insertion elites (superior individu) would be conducted by reproduction operator of GA. Meeting individu for solution if the fitness value of objective function is 1.00 (100%) for all of individu tested in a generation.

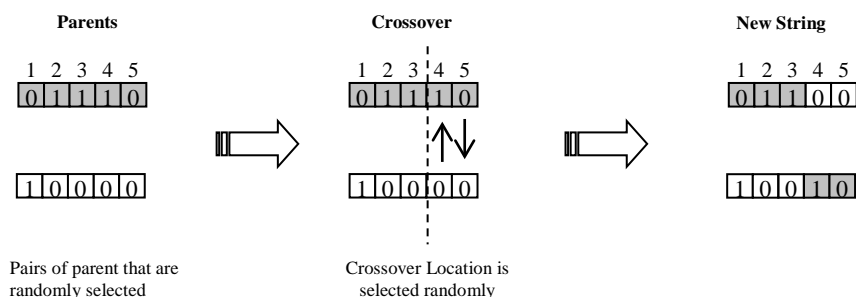


Figure 4 Simple Crossover Operator

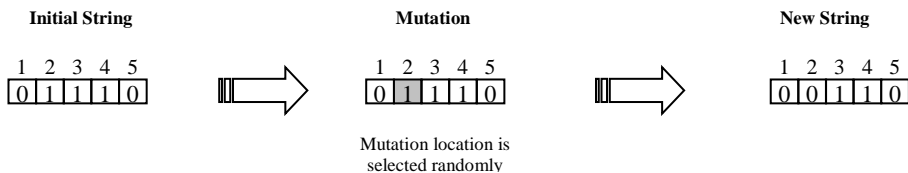


Figure 5 Simple Mutation Operator

By virtue of its simple ability, GA method will be used to look for optimum solution that satisfies the objective function above. The GA procedure (Frazilla, 2005) shall be as follows:

- Step 1 : (Initialization)
 - Generate the initial population (a set of random strings) and set the number of generation $(g) = 0$
 - Step 2 : (Fitness computation)
 - Determine the fitness value of each individual in the population
 - Step 3 : (Evolution)
 - perform reproduction
 - perform simple (single point) crossover
 - perform mutation
- Set $g = g + 1$

Step 4 : (Repetition)

If the termination condition is satisfied (i.e. number of generation = maximum number of generation), determine the fitness value of the last generation and stop. Otherwise, go back to Step 2.

4. A MODEL TESTED ON HYPOTHETICAL NETWORK

Verification of network model proposed uses hypothetical data of urban freight transport network as described in Figure 6. According to the figure, the tendency of the best selection result of a set of freight path is already ascertained. This road network representative as proof of the empirical problem because it has adapted to the characteristics of the roads in urban areas

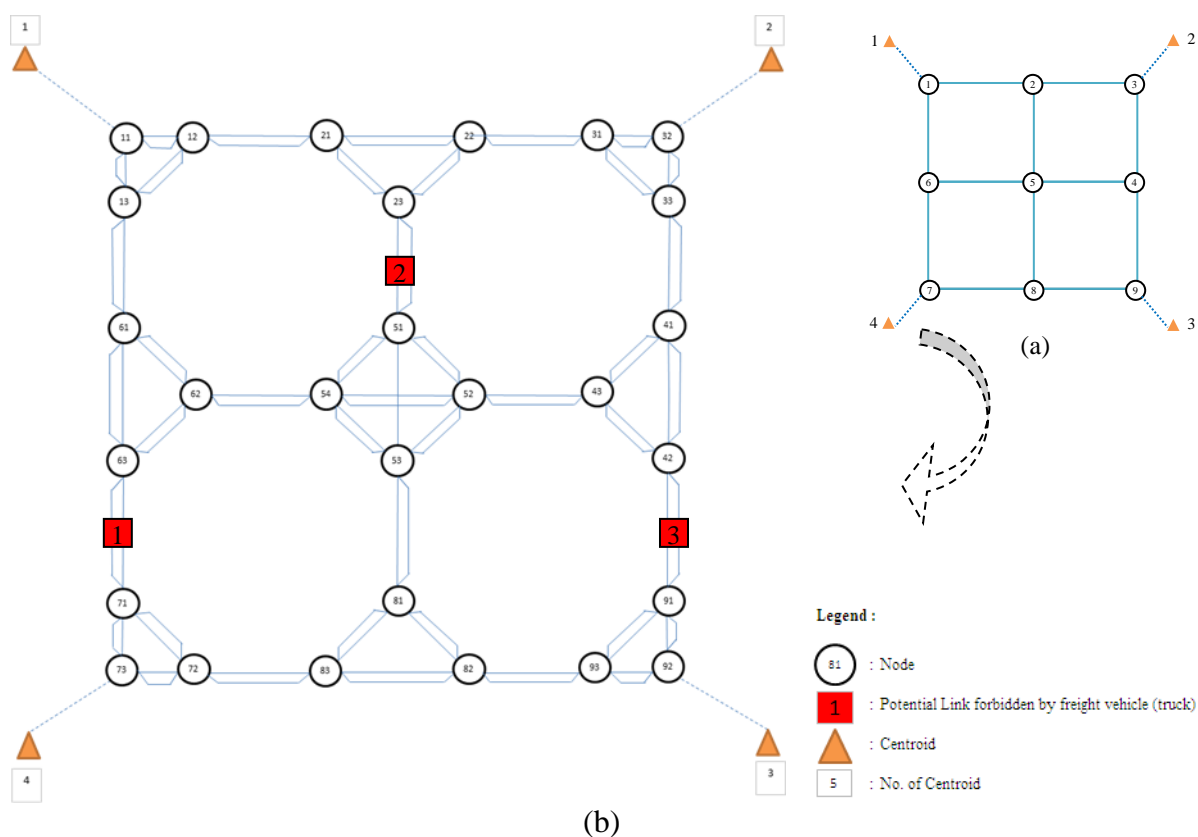


Figure 6 Hypothetical Road Network Model

A Node on Figure 6a is a representation of a junction. It is exploded to make a link representing vehicle movement from each approach of a junction (see Figure 3 and 6b). They are two types of node representing two types of intersection based on the type of their control, They are signal and unsignal intersection. We assume that they are two (a junction with 3 approaches) and three (a junction with 4 approaches) movements of vehicle from one approach of a junction. Here are left turn, through and right turn movement. In our models, each of them is set as a direction of link as well as their direction.

A link on our model represents one direction of roadway. One line in Figure 6 represents two ways of roadway, except it is only one way. A link connect among two nodes

with one way of road. If a line on the picture in Figure 6 represent a two ways of roadway in fact, it would be coded as two link which have a different direction. The picture on Figure 6 is just a simplification of complicated link that should be presented on the picture.

The hypothetical Network above consists of 12 road links, 9 intersections and 4 centroids. The representation link at link road is as described in Figure 2 and 6b, and the link at node points (i.e. intersection) is as described in Figure 3 and 6b. The link number :71-63 ; 61-13 ; 12-21 and 22-31 are assumed to have higher capacities, and the link number of 33-41, 42-91, 93-82 and 83-72 are assumed to have middle capacities, whereas the other links are assumed to have smaller capacities than the others. Every road link is specified to have the same length. The intention of those assumptions is to make it easier for model result verification.

Table 1 Alternative Roads Can Be Opened / Closed (Truck Traffic Limitation Scenario)

No.	Alternative groups Roads Opened / closed	Roads are opened / closed
1	1	63-71 dan 71-63
2	2	23-51 dan 51-23
3	3	42-91 dan 91-42

Table 2 Travel Demand of Freight and Passenger

Origin	Destination	Travel Demand	
		Freight (ton/day)	Passenger (pass/day)
1	2	10000.0	15000.0
1	3	9750.0	14750.0
1	4	9500.0	14500.0
2	1	15000.0	35000.0
2	3	14500.0	34500.0
2	4	14000.0	34000.0
3	1	20000.0	30000.0
3	2	19750.0	29750.0
3	4	19500.0	29500.0
4	1	15000.0	25000.0
4	2	14750.0	24750.0
4	3	14500.0	24500.0

There are three groups of alternative roads that could potentially be applied to open / closed to truck traffic, as shown in Figure 6b and Table 1, hereinafter referred to as alternative roads are opened / closed. Of the three alternatives of these roads, will further develop into 7 (2^3-1) combination of alternative roads are opened / closed to truck traffic. This option is one of the tactical management of freight are often applied in urban areas. The network database structure needed for urban freight transportation network design is classified into 3 parts: base network, network for freight vehicle and network for passenger (other user) vehicle. The database for the network consists of the data such as: number of nodes, number of links, link position prohibited for freight (i.e. truck), link type, link direction (lane), link length, link capacities, free flow speed, other traffic volume, number and type of junction, green time and cycle time. Meanwhile, the specific network data for freight and passenger vehicle are link

location/position prohibited for freight, travel time for free flow, parameter $\emptyset 1$, and $\emptyset 2$, vehicle capacities, tariff, time value for goods and passenger.

Travel demands for freight and passenger are described in Table 2. According to Table 2, there are 4 OD (origin and destination) pairs for each of freight and passenger (daily trip). Here, freight vehicle (truck) is assumed to be able to transport 10 tons of goods every one transporting, whereas passenger vehicle could transport 3 passengers for each time of transporting. Passenger cars equivalent for freight and passenger vehicle are 2,5 and 1.0 respectively. Travel demand assigned will be 10% on peak hours. This factor is assumed to be based on the peak hour fact of traffic flow's going on in an urban area in Indonesia as mentioned in Indonesian Highway Capacity Manual, 1997.

5. RESULT

Model durability testing of freight transport network optimization using the GA procedure requires some GA parameter values. The values for genetic operators that will be used are based on the findings of previous studies (e.g. Goldberg, 1989; Taniguchi *et al.*, 1999, Yamada *et al.*, 1999). The length of the chromosome is assumed to be 3 (based on the number of scenario action), the rate of crossover is set as 0.6 and the mutation rate is set at 0.03. The number of elite maintained at every generation is 1 (one), while the number of individuals is set as 30 (thirty) in each generation. The number of generations is set as many as 30 generations.

The number of individuals set as many as 45 in this research is based on the model testing from 5 generation up to the 50 generation as depicted in Figure 7. In the picture in Figure 7 it is known that the convergence of the expected achievement of the objective function occurred in the population with any pop size tested in the 30th generation. This population number is important for ensuring that the solutions expected are not stuck at a local optimum. Achieving the maximum objective function value can be achieved from the first generation (see Figure 7), and the convergence of the achievements can be seen starting at the 30th generation, as shown in Figure 7.

Optimization of urban freight transport network with GA method as solutions technique provide effective results significantly. Such results can be obtained for any initial random number and number of individuals (population size), the amount of a certain generation. Here in Figure 7 delivered the performance of the method GA for random combination of seed number 9.

Based on Figure 7 it can be seen that the computation for the initial testing of the model with seed random numbers 9, convergence for all the population size (pop size) began to occur in the generation number 30. The population size (pop size) that achieve convergent with the smallest generation number is 10, which started to converge on the number of generations reach 5. While the size of the population that achieve convergent with the largest generation number is 15, which began converging on the amount of generation reaches 30. having regard to the testing results of the model can be concluded that the model has generated a high level of effectiveness with convergence significant.

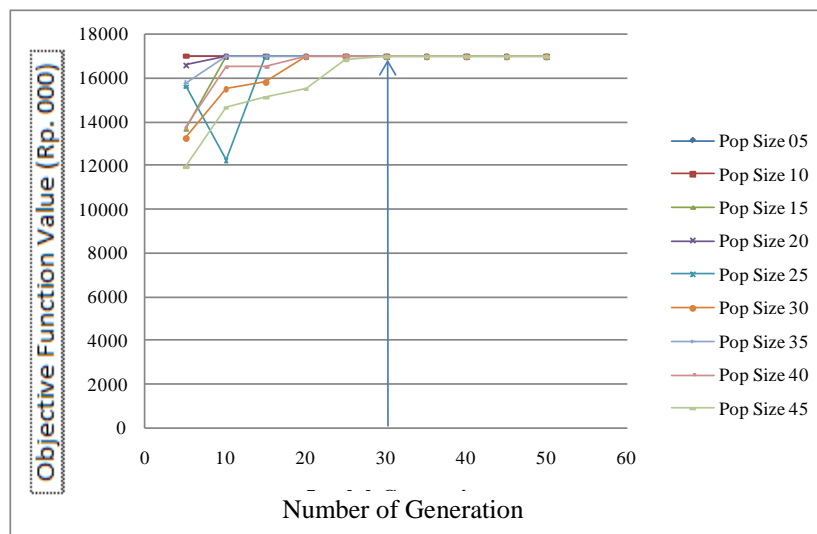


Figure 7 Effect of Number of Population on The Convergence of Objective Function Values (seed random=9)

GA procedure includes some random processes; use of a set of random numbers (determined by random initial values or seed randoms number) will affect the computational results. To check the stability of the results due to differences in the initial random values, there should be an investigation of several different random initial values. Testing the consistency of the model with different random initial values to the achievement of the maximum values, is done by repeating 1800 times as shown in Table 3.

Based on the result in Table 3, known the appearance speed of optimum objective function values on each parameter combinations. It can be seen on the combinations of total individu (pop size) = 5, total generation = 5 with seed random of 9, 12 and 17. In this case, it is concluded that smaller GA parameter-values combination tested, faster time needed for testing process and vice versa. However bigger the number of test parameter combination, it is not guaranteed the result of optimum function value can be appear faster.

The optimum solution of the result computation speed performance of goods transportation network design on this hypothetical network case can be seen in the Table 4 and Table 8. It is known that computation time needed to calculate network design optimisation on hypothetical network with the suggested method is very short time, less than 1 (one) second. The average of computation time is 0,52 second, the highest is 0,72 second and the lowest is 0,30 second. If it compared with manual calculation (conventional), by calculating on 7 alternative combinations of open/close the roadway like in Table 1, the time needed more than 10 minutes for 1 alternative roadway combinations. It is because have to do the inputing manually on each roadway alternative combinations in the network database one by one.

This very short computation time will increase with the network complexity and the total of roadway alternatives that can be opened and closed. It is determine iteration time on traffic assignment (lower level), whilst the number of roadway alternatives that can be opened and closed will determine the length of cromosom, and it is increasing the number of alternative combinations exponentially, which mean adding more calculation time to decide roadway alternatives to meet the purposed function expected (upper level).

Table 3 The Performance Achievement of Objective Function Optimum Value of Freight Network Optimization Model (Minimum Number of Generation)

Seed Random	Pop Size								
	5	10	15	20	25	30	35	40	45
	Num.Gen	Num. Gen	Num. Gen	Num. Gen	Num. Gen	Num. Gen	Num. Gen	Num. Gen	Num. Gen
1	10	5	5	10	5	20	20	20	20
2	10	5	10	10	10	15	15	20	25
3	-	10	5	10	20	15	20	25	30
4	-	5	20	15	25	30	15	10	10
5	10	10	-	20	10	15	20	20	30
6	-	-	-	-	-	15	15	20	25
7	-	-	5	20	20	10	20	20	25
8	10	5	5	10	20	10	15	15	20
9	5	5	10	10	15	20	15	20	30
10	-	-	-	-	-	-	10	20	25
11	10	5	10	15	5	20	15	20	-
12	5	5	10	10	25	15	20	20	20
13	10	5	5	15	10	15	15	35	20
14	-	5	10	10	15	20	15	30	15
15	-	15	10	10	20	20	20	25	25
16	-	-	-	15	30	15	15	25	20
17	5	5	5	30	20	10	10	15	20
18	-	-	-	-	-	-	-	45	30
19	-	-	10	10	10	25	15	40	15
20	10	5	10	15	15	20	35	10	25

Legend :

Pop

Size

Num.Ge

n

Seed Random

: Number of individu in 1 (one) generation

: Number of generation on one time of simulation

: random initial values

Related to the length of the cromosom, Frazila (2005) stated that beside above GA parameters, the result of optimum purpose function value is also affected by the decision of the cromosom length tested, indicates the number of action alternatives. In the real network conditions, the number of cromosoms represent the number of roadway alternatives that can be opened and closed may simply more than three, therefore, the speed result appears optimum purpose function value in this test does not guaranty will give same result if it is applied on the real network. So that it is to be done a selection of parameter combinations with this result as a reference.

Table 4 Time Computing Program Achieving Optimum Value of Objective Function (second , seed random=9)

Jumlah Generasi	Jumlah Individu dalam 1 generasi (Pop Size)								
	5	10	15	20	25	30	35	40	45
5	0,34	0,46	0,52	0,41	0,56	0,53	0,50	0,69	0,55
10	0,37	0,52	0,49	0,51	0,59	0,55	0,59	0,59	0,57
15	0,43	0,47	0,40	0,47	0,62	0,47	0,56	0,56	0,57
20	0,36	0,46	0,44	0,50	0,60	0,48	0,66	0,58	0,54
25	0,36	0,51	0,50	0,45	0,49	0,51	0,46	0,72	0,54
30	0,38	0,50	0,44	0,47	0,57	0,54	0,53	0,52	0,62
35	0,30	0,53	0,49	0,43	0,54	0,53	0,60	0,54	0,55
40	0,33	0,41	0,55	0,48	0,61	0,63	0,59	0,57	0,61
45	0,35	0,43	0,55	0,54	0,57	0,62	0,65	0,61	0,56
50	0,36	0,48	0,43	0,49	0,48	0,67	0,57	0,59	0,63

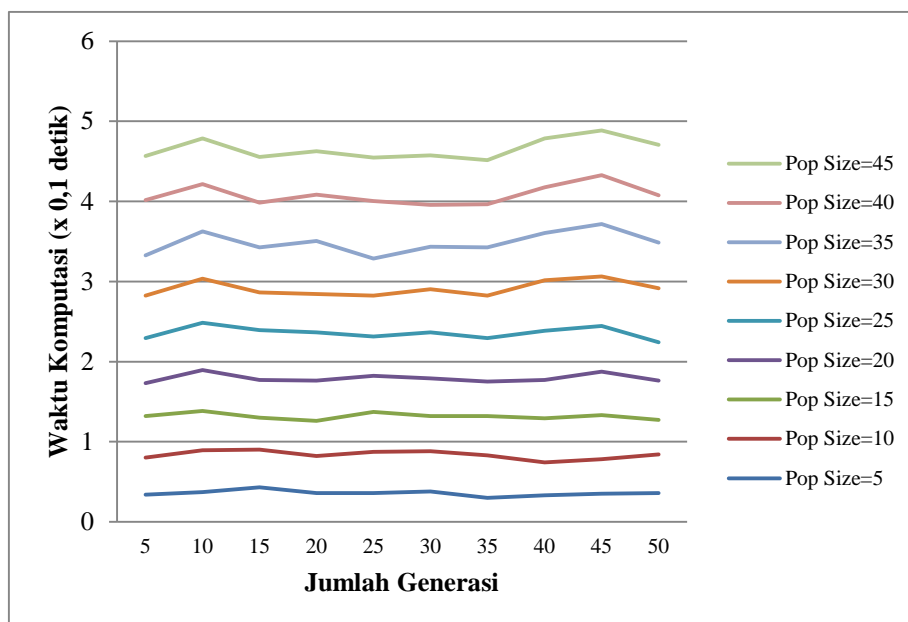


Figure 8 Time Computing Program Achieving Optimum Value of Objective Function (second , seed random=9)

The test results in combination with the above parameter indicates that optimization model GA on pemrograman bi-level gives an indication of optimum achievement of the objective function the same on every initial random numbers tested. What distinguishes the results of optimization models in a variety of initial random numbers is the achievement of the objective function value optimum combination of parameters occurs in the pop size and number of different generations. In addition, in the test with hypothetical network, the time required to achieve the optimum objective function value for each combination of parameters GA is relatively short. This shows that freight transport network optimization model proposed robust, that is effective and consistent in the achievement of the objective function value (effective) and fast in the achievement of these values (efficient).

6. CONCLUSION AND DISCUSSION

According to the result of this research, the technical solution to this assignment mechanism through diagonalization at the lower level is effective for finding the solution of multimodal multiuser traffic assignment whose cost function of matrix for every user is non-separable and Jacobian asymmetric. To make it closer to the reality, the link cost function at a junction should be more complex according to the complexity of its approach configuration and control type. The model of link for representing vehicle movement can represent a vehicle movement at a specific lane.

GA procedure provides a good solution in the freight network design in urban areas. This idea is based on a model sustainability, which is quite significant. However, under conditions where the initial random values were differentiated (and at the population size = 45, and the number of generations = 50), the GA procedure was able to maintain the convergence on the global optimum objective function value

The global optimum value was achieved when the random initial value was set for every seed number. In this simple network level, the rate of mutation and crossover provide a positive influence on the convergence of achieving a global optimum objective function value. Proof of higher convergence at the higher level of road network resolution needs to be tested again, whether the modeling using GA procedure will still be able to provide convergence of achieving the global optimum objective. With regard to the results of the network design, the scenario action selected from the results of modeling using GA procedure was very relevant to the design of the hypothetical road network properties. Properties of road network was deliberately designed to lead to the expected solution so that it is easy to verify the success of the modeling results.

Based on the research result, heuristic method of GA (Genetic Algorithm) is able to provide an efficient set of the best freight path in the urban road transportation network system. The proposed optimization model has proved robust.

Given the combination of alternatives open / closed is raised as much as $2^n - 1$ (n, the number of alternative roads that can open/closed), the use of this GA method works efficiently in case of a hypothetical network. Population size and the number of effective and efficient generation depends on the size of the network to be optimized and the number of alternative roads that can open/closed. Therefore, for the application of the model on a larger network to be checked again and the population of individuals that effectively and efficiently. The need to set the number of generations and the number of people (population) is to make savings of computing time on a real network because the larger the population size and the number of generations, the time required for computing the longer optimization.

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