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Optimization Modeling of Urban Freight Transportation Network by Using a Metaheuristic Approach, Genetic Local Search Procedure

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Abstract

Creating a transportation network that reduces the cost of urban freight is highly challenging. Freight route is determined by the amount of congestion generated by the vehicle type. Furthermore, it must compete with other users to locate the optimal path for their traffic on the city's restricted road network infrastructure system. Freight network routing begins with identifying and determining the optimum route. The freight network is optimized by introducing a heavy traffic restriction mechanism in metropolitan areas, and an attempt is made to propose a set of routes as a set of freight traffic modes. The primary goal of freight routing in this research is making a freight network model optimization to find a set of freight routing by optimizing (efficiency) trip prices due to limited road infrastructure and the difficulties of constructing road infrastructure in metropolitan areas. Therefore, selecting a group of routes as the journey of the commodities is a realistic alternative to minimizing costs. The problem of route selection is one of combinatorial optimization. The challenge is to narrow the pool of action options to a set of recommended actions. Due to vehicle characteristics and traffic flow, route selection carefully considers vehicle behavior. A two-level mathematical model that was created by formulating route options served as the framework for the research. The combination of chosen routes is maximized using a genetic algorithm such as a Genetic Local Search. The model is examined via its application to a fictitious network. The result converges to the target value of 246,311.9 IDR. It shows that the model satisfies the convergence condition of producing in 0.76 seconds. As a result, a model with a genetic local search technique that can search more effectively in the city's freight network's ideal path is created. The GLS combinatorial optimization model shows us it could find the best set of urban freight networks with the best performance. This is consistent with Yamada et al. GLS methods perform well in solving combinatorial problems.

Keywords: *Route selection, Urban freight transport network, Multiuser class, bi-level programming, Genetic Local Search*

INTRODUCTION

Many countries use freight routes in general urban areas to transfer cargo. It is considered a freight route in Indonesia for conveying public commodities utilizing heavy vehicles such as B. Truck to Trailer with two axles. Its end destination is in a city region, and its mobility is normally limited by the route parameters that allow or prohibit it. Freight route is determined by the amount of congestion generated by the vehicle type. Furthermore, it must compete with other users to locate the optimal path for their traffic on the city's restricted road network infrastructure system. As a result, freight network routing begins with identifying and determining the optimum route.

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According to Castro and colleagues, the freight network is optimized by introducing a heavy traffic restriction mechanism in metropolitan areas, and an attempt is made to propose a set of routes as a set of freight traffic modes (Crainic et al., 1990b). The proposed strategy is appropriate for metropolitan settings since it minimizes traffic congestion as well as NOx and PM emissions per unit of time on the road.

The primary goal of freight routing is efficiency (Taniguchi et al., 2001). Due to limited road infrastructure and the difficulties of constructing road infrastructure in metropolitan areas, operators must compete with other customers to decide the optimum trip prices. As a result, freight network planners should plan routes and select the optimum approaches for their fleets to maximize transportation effort.

In this situation, route selection is a combinatorial optimization problem. The problem is to identify and pick a set of recommended actions from all potential options. When picking a route, the vehicle's behavior is carefully evaluated, taking into consideration its attributes and traffic flow. This research aims to make a freight network optimization model by selecting a set of freight networks as a decision variable to find a set of freight routing by optimizing (efficiency) trip prices due to limited road infrastructure and the difficulties of constructing road infrastructure in metropolitan areas. In the formulation of the path selection model, this study creates a two-level planning framework and a mathematical model. During the scene development, route combinations will be developed using a meta-heuristic approach termed genetic local search.

LITERATURE REVIEW

Taniguchi developed the concept of urban logistics within a two-tier framework in urban areas (Taniguchi et al., 2001). Nonetheless, other users' traffic behavior has not influenced the operator's behavior. Two-level planning is a two-level decision-making process in which decision-makers behave when determining the optimal cargo path, with a lower and upper level. Operators and other users interpret traffic behavior as an attempt to replicate reality in a modeling framework. The higher layer depicts the targeted decision-making behavior in a particular analytical procedure. Taniguchi et al. created the urban logistics vehicle routing problem (Taniguchi et al., 2001). The routing strategy you suggest is solely cost-based and does not consider other network users' behavior. According to further researchers, such as Russ et al. (2004a; 2004b; 2005) and Yamada et al. (2010), routing is established for commodities that are impacted by dynamic traffic flow caused by other user activities (Taniguchi et al., 2001). Furthermore, Frazilla and associates, for their network models, multimodal and multiuser classes have been taken into consideration (Russ et al., 2004b). All of these researchers used a two-level programming framework to create their models.

At the highest level, a methodical approach to constructing freight networks with clear objectives represents the decisions made by policymakers. Fix the objective function for choosing vehicle routes, considering their effect on air pollution, i.e., NOx, in the framework of the model created by the top layers in 2009 (nitrogen oxides). The multi-agent notion is given the two-tier principle, and genetic algorithms are used to create the best route selection process (GA). Russ et al. (2005) and Yamada et al. (2010) noted GA improvements. There are three approaches to tackling two-level programming combinatorial optimization problems: rigorous approaches, approximation approaches, and meta-heuristic approaches. Over the past ten years, several meta-heuristic methods have been created and used in soft computing environments. This method addresses challenging network difficulties that arise in sophisticated mathematical programming challenges (NP-hard problems). Although this method can deliver somewhat useful answers, it does not ensure accuracy for the ideal solution. As a result, this approach is typically used to solve combinatorial optimization issues where it is challenging to pinpoint the precise outcome of the best possible solution. GAs is employed and developed in many variations among combinatorial optimization metaheuristic techniques because of their dependability in problem solutions. However, different metaheuristic problem-solving methods might deliver superior outcomes.

Holland (1979) was the first to propose the meta-heuristic technique known as genetic algorithms based on genetic and natural selection principles. A chromosome, or an individual, is one possible solution. Every chromosome site is referred to as a gene, and the gene value is designated an allele value. The binary value of "0,1" most frequently represents the allele value. Some people might decide to work as a team. Starting with a random population of chromosomes representing several solutions to the problem, the best one is chosen. A population of chromosomal members is assessed using a predetermined fitness function and a fresh set of populations produced by genetic operators. For each generation, use local search. It will then assess each population's remaining capacity using a fitness function and, using straightforward operators, build a new set of chromosomes from the artificial population (selection, reproduction, and mutation). Some GA applications for optimization issues are covered by Goldberg (1989). The field of transportation makes extensive use of GA. To connect design with urban parking issues, Cantarella and Vitetta used GA in multilevel programming (Cantarella, 1994). A broader perspective uses genetic approaches to evaluate novel road network topologies. Along with the traffic distribution procedure, an iterative approach is used to interpret traffic distribution on sets of traffic signals and connections at the core level. The traffic signals, network delays, and transient flows are calculated in a loop until the two successive traffic flow patterns are controlled within a predefined tolerance.

The Cumulative Genetic Algorithm (CGA), a fixed variant of GA, and its use in constructing transmission networks were suggested by Xiong and Schneider (1993). For reproduction in CGA, all population members with good fitness ratings are retained and merged with fresh population members. Artificial neural networks are also used in this item to produce a collection of people (parents) who are distinct from the previous generation. Kwan and Wren proposed further hybrid genetic algorithms that they used to solve the bus driver scheduling issue (Kwan et al., 1994). They merged integer programming, a rule based on predictions of driver performance, and GA.

Utilize GA to create the ideal population, then use integer programming to create the ideal driver strategy. Yamada and co. The GA approach is used to determine the size and location of the ideal logistics terminal (Yamada et al., 1999). Advanced (elite) operators also develop the algorithm's performance. For usage in the following generation, this operator selects the population's best people (such as chromosomes with high functional fitness). The Vector Evaluation Genetic Algorithm, or VEGA, is a multi-objective study utilized in the development of genetic algorithm models as well (Yamada et al., 2010).

In the case of studying freight networks using other two-tier programming frameworks, Liao et al. (2010) studied multimodal transport and multi-activity trip planning. Intermodal and multi-activity travel planning is a practical but thorny problem in transportation research. This paper develops an improved hyper-network model to address this issue. The supernetwork is mainly constructed in three steps: first, the personalized network is divided into two types of networks, and all connections are mode-specific; then, starting from the initial active state, these are assigned to all possible active vehicle states through state propagation. Finally, these discrete networks are connected into a supernetwork through state-labeled transition links. The proposed supernetwork is easier to construct than previous proposals and reduces the size required to include all selected face combinations explicitly. It can be shown that for every active program, every tour in this representation is a feasible solution. Thus, each transport and transition connection can be defined as dependent on mode and activity status; thus, standard shortest-path algorithms can be used to find the ideal route. The case study demonstrates that real-time supernetwork models can be applied to practical voyage planning.

Still relevant to supernetworks is a paper by Yamada et al. (2020) that proposes a supply chain-transportation-supernetwork equilibrium model (SC-T-SNE) that considers the inventory costs. This model is also a modified version of the supply chain network equilibrium model, which deals with supernetworks that explicitly integrate supply chain networks (SCNs) with transportation networks. Inventory costs are estimated from probability distributions to represent demand changes, where wholesalers and/or retailer preferences for inventory can be represented by setting thresholds. The decentralized decision-making process and interactions among manufacturers, wholesalers, retailers, consumers (demand markets), carriers, and transportation network users are integrated into the model. These have been formulated as variational inequality problems, and the equilibrium conditions for hyper networks and solutions to the variational inequality problems are given. The results of the model, applied to a hypothetical supernetwork, show that increased variability in consumer demand will reduce the number of products traded between entities and the efficiency of the SCN. Numerical tests using this model also show that sharing information about this demand variability between wholesalers and retailers can improve the efficiency of SCNs as their distribution channels change. Furthermore, it was noted that the degree of impact achieved through information exchange is comparable to that achieved through increased capacity on congested sections of the road network.

Urban loading and unloading lots are often overcrowded, shifting delivery operations onto driveways and sidewalks, increasing traffic flow, generating noise, and causing pollution. Regarding local search, in this study, Mrazovic et al. (2018) proposed routing optimization based on data analysis to improve the utilization of vehicle traffic and parking spaces. They have formalized this new problem and developed a novel multi-vehicle route planner that avoids crowded loading and unloading areas and minimizes the total duration. They presented the developed tool and provided illustrations and analysis for Urban Freight in Barcelona, which monitors tens of thousands of daily deliveries. Their system efficiently evaluates candidate routes by incorporating waiting times and further delays for drivers other than first-class citizens into the optimization. A two-layer local search using a greedy stochastic adaptive method for variable neighborhood search is proposed. Their method will be applied and validated on data collected by the Barcelona Urban Freight Network, which includes 3,704,034 parking events. The results show that the solution has significantly improved the use of available parking spaces and vehicle traffic. The analysis also provides useful insights into delivery routing and parking space management for sustainable urban freight and urban logistics.

Intermodal freight networks play a vital role in maintaining the flow of goods across industries and geographies. As a result, the impact of a large-scale disruptive event could lead to the closure of essential transport hubs and connections, which could lead to disruptions in the flow of goods and major disruptions in industries that depend on these commodities to increase economic productivity. According to Darayi et al. (2019), their study combined multi-commodity network flow formulation with economic interdependence model to quantify the cross-industry impact of traffic network disruption to formulate conditional diversion plans to enhance network Adaptability. The formulation proposed in their study is illustrated through a case study of Freight Planning in Oklahoma, which considers an outage scenario where a network component is lost and how the proposed approach improves overall productivity after an outage.

As Jiang (2022) mentioned, multimodal transport has received more and more attention because of its cost-effective features. Choosing a reasonable transportation plan can effectively control transportation costs. Considering that both railway and waterway transportation have fixed timetables in real life, this paper establishes a multimodal transportation route optimization model aiming at minimizing the total transportation cost, which consists of transportation cost, transit cost, waiting for time cost, and CO_2 emission cost components. To solve the model, a genetic algorithm based on conservation and immigration strategies is used. A case study demonstrates the model's effectiveness, providing decision support for selecting intermodal transport options.

RESEARCH METHOD

In this paper's two-level planning framework for developing the urban freight network, the problem is represented by administrator behavior in the top layer and operator and other user behavior in the lower layer (Chiou, 2005). User equilibrium is the driving behavior model used by freight companies when deciding which routes to apply to the underlying road network. The choice of the road segment freight vehicles can travel through by imposing a ban on the road segment that freight vehicles can travel through is the variable for this decision. The achievement of the least goal function of the overall transportation cost of the higher layer-created scenario determines the choice of the collection of routes. Aiming for little network effort is a goal in itself. The technical approach that the top layer suggests incorporates this objective. The meta-heuristic known as genetic local search is the optimization method employed at the top layer.

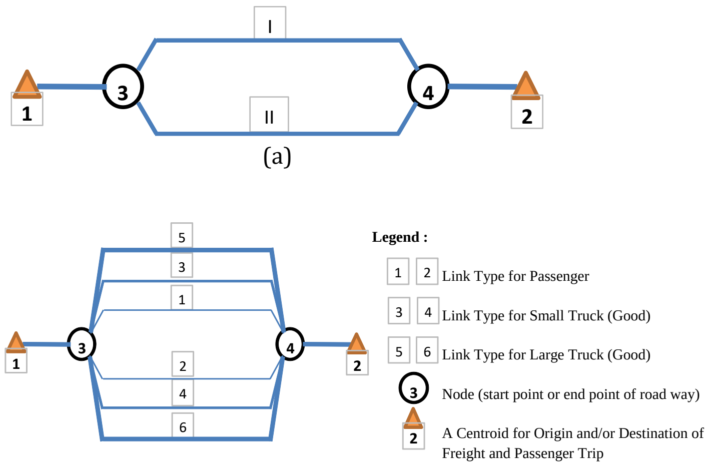
The design of the freight transportation network optimization model proposed above needs to be verified; therefore, a certain amount of data is needed. The data required includes the matrix of the origin and destination of freight transport, including passengers. These data are obtained from simplified secondary data. Using the current actual data, the data can be obtained by conducting interview surveys of freight and passenger transport companies, interviews with freight owners, and passenger interviews in housing, commercial areas, and on the roadside. In addition to the matrix data on the origin and destination of freight (passenger) transport, data on the characteristics of road transport traffic are also needed, which include road capacity, vehicle speed, and road length. Because this data is to verify the proposed model, it is deliberately designed so that the exact verification results can be predicted correctly. This data is processed by considering the Indonesian road capacity manual standards.

FINDINGS AND DISCUSSION

Lower-Level Problem

Transport Network Representation

Start and end nodes are typically used to illustrate a road network. Two road links are shown in the road network in Figure 2 (Road Links I and II). These linkages connect a pair of nodes (3 and 4) that may be routed from starting area 1 to destination area 2. Whether it is a passenger or a freight car, the road is in a condition that allows a vehicle to pass. Exploded links 1, 3, and 5 on road link I and links 2, 4, and 6 on road link II alternately represent the road segment model. An abstract network model G(N, A) describes this network representation, where N denotes a set of nodes and A denotes a set of links.



(b)

Figure 1. Representation of Urban Road Transportation Network

Examples of intersection nodes are nodes 3 and 4. An investigation of urban planning was done in this situation. As a result, delays at crossings become a highly important issue that requires more thorough consideration. Figure 3 depicts the traffic flow at the crossroads in light of this. The throughput capacity and flow characteristics will be considered to estimate the delay time.

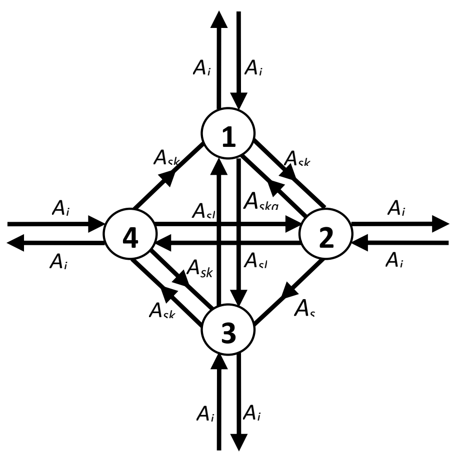


Figure 2. The Representation of Traffic Movement at a Junction

Regarding this representation, the set of links A is made up of road links (A_j), a signalizing left turn link (A_{ski}), a signalizing through link (A_{sl}) a signalizing right turn link (A_{ska}), a signalizing left turn link priority (A_{pki}), a signalizing through link priority (A_{pl}), and a signalizing right turn priority (A_{pka}), as well as centroid connectors (A_c), so that $A = A_j \cup A_{ski} \cup A_{sl} \cup A_{ska} \cup A_{pki} \cup A_{pl}\ A_{pka} \cup A_c$.

According to the operation control type, priority, and signal type of an intersection, it is divided into two types. The Indonesian Highway Capacity Manual, 1997 approach was used to synthetically determine the delay time for each intersection (Public Work of Departement of Republic of Indonesia, 1997).

Link Cost Function

The link cost is the constraint that vehicles pass through the link. The cost of connection for user type i is expressed as a generalized cost consisting of component tariffs and travel time costs, as shown in Equation (1) (Yamada et al., 2010). The time component is the result of multiplying the delay time and time values for each user type.

$$c_a(x_a^i) = \rho_a^i + \alpha^i d_a^i(x_a^i) \tag{1}$$

Where:

ρ_a^i : Rates of user type i on link a (IDR)

α^i : Time value for user type i (IDR/hour)

$d_a^i(x_a^i)$: Delay time of user type i on link a (hour)

The time-consuming component fluctuates depending on the connection type and is traffic-dependent, whereas the tariff component has a constant value. In this case, the connection types are distinguished as links representing roads and representing movement at intersections. Furthermore, in traffic modeling, traffic distribution is differentiated between two connection types based on user type. Use polynomial estimations for all connection types to prevent this complexity or non-singular solution, as illustrated in the equations (2) (Crainic et al., 1990a; 1990b):

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

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

$d_a^i(x_a^T)$: delay time of user type i on link a

Solution Technic

In traffic allocation models, User Equilibrium (UE) techniques based on the idea of user-optimal wardrops are employed (Sheffi, 1985; Vliet, 1978; Vliet, 1987). UE flow can be considered a solution to the convex cost minimization problem in the scenario where the Jacobian matrix of the link cost function is symmetric. This study makes different mode and routing decisions for freight trucks and other users as a multiuser class. The multimodal network is transformed into a single-modal abstract network to perform traffic mapping. Therefore, an inseparable and asymmetric Jacobian cost function matrix between user types can address the UE problem. A variational inequality (Dafermos, 1980) can express how the aforementioned flow distribution model is represented. The formula is as follows:

$$\text{find } x_a^{i*} \in K, \tag{3}$$

So that:

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

Where x_a^{i*} is UE flow on link for user type i, and $\tilde{x}$ is a coloum vector dimensional p with components $\{x_a^1,\ldots..,x_a^p\}$. K is defined as $K \equiv \{\tilde{x}$ | satisfying link flow and non-negative conservative flow. $c_a^i(.)$ is generalized cost on link for user type i, and A is set of links on road transportation network. Since multiple users are assigned, this case is considered as a multi-class UE assignment problem with an inseparable and asymmetric cost function. A widely used method to address such cases is diagonalization (Florian & Spiess, 1982).

Upper-Level Problem

Objective Function

The goal is to maximize network development's benefits when the existing state's internal cost differs from the network solution through the developed scenario. The formula for this function, which accounts for the time spent in the road network system and the running expenditures of the vehicle, is as follows:

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

Where:

x_a^{i*} : link flows of each user type that are the solution to the UE problem with the combination of actions implemented (vehicle/hour)

$c_a^i(x_a^i, y_a)$: generalized cost on link a by user type i that depends on the equilibrium flow and whether the actions are implemented or not (action implementation indicator y_a) (IDR)

Solution Technic

As mentioned earlier, the top-level problem is a combinatorial problem, and the proposed optimization solution technique is a heuristic for genetic algorithms. The method used by GA is very simple. It is no more complicated than duplicating or swapping some of a person's chromosomes. On the other hand, simplicity of operation and influence strength are two characteristics of genetic algorithms that make the method very attractive. The most commonly used basic operators in genetic algorithms are replication, crossover, and mutation.

Yamada, Frazilla, and Castro developed three combined GA solution techniques, such as Simple Genetic Algorithm (SGA), Genetic Algorithm Improved with Additive Operators (GA-I), and Genetic Local Search (GLS) (Yamada et al., 2010). From the three schemes of GA, GLS outperforms the other schemes. For the same investigation, GLS outperforms all other heuristics, such as tabu and random searches.

GLS, also known as the meme algorithm, is a method that combines local search techniques with genetic algorithms (Yamada et al., 2010). Though GA can efficiently locate the proximity of the ideal solution from a larger area, GLS can compensate for GA's shortcomings in small area searches. Additionally, during the mutation stage of the GA-I process, a local search operator that switches neighbors is added (see Figure 5). Randomly chosen genes are exchanged for their alleles in neighboring genes in each individual (Russ, 2005).

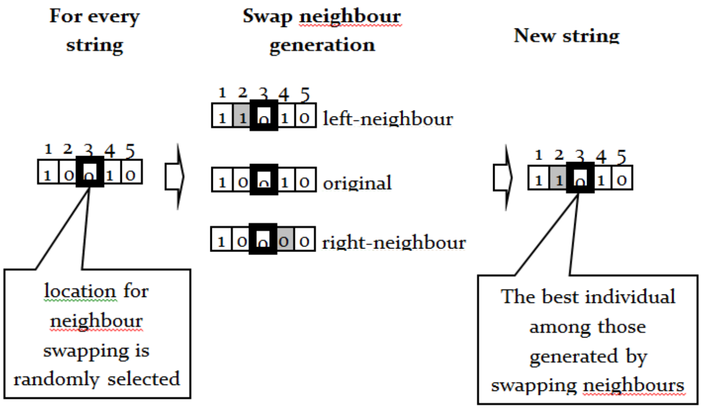


Figure 3. Local Search (Swap Neighbour) Operators

Along with the initial person, three additional people can be produced using this method. The best of the three people is chosen, and they are passed on to the following generation. The GLS method's algorithm is as follows:

Step 1 : (Initialization)
Set the number of generations (g) to 0 and create the starting population, which should be a collection of random strings.

Step 2 : (Fitness computation)
identify each person's fitness level throughout the population.

Step 3 : (Elite preservation)
Determine how many people (or how many elites need to be preserved) have a high fitness value.

Step 4 : (Evolution)
- perform uniform crossover
- perform creep mutation
- perform the local search

Step 5 : (Reproduction)
- determine the fitness value of each individual in the population resulting from the previous step
- perform reproduction accordingly
  Set g = g + 1

Step 6 : (Elite insertion and repetition)
- Insert the elites from Step 3 into the new population
- If the termination condition is satisfied, determine the fitness value of the last generation and stop. Otherwise, go back to Step 2.

Model Application

To validate the network model, hypothetical data for the urban freight network depicted in Figure 4 is recommended. In Figure 4, it has been possible to identify trends in the best election results for multiple freight train paths.

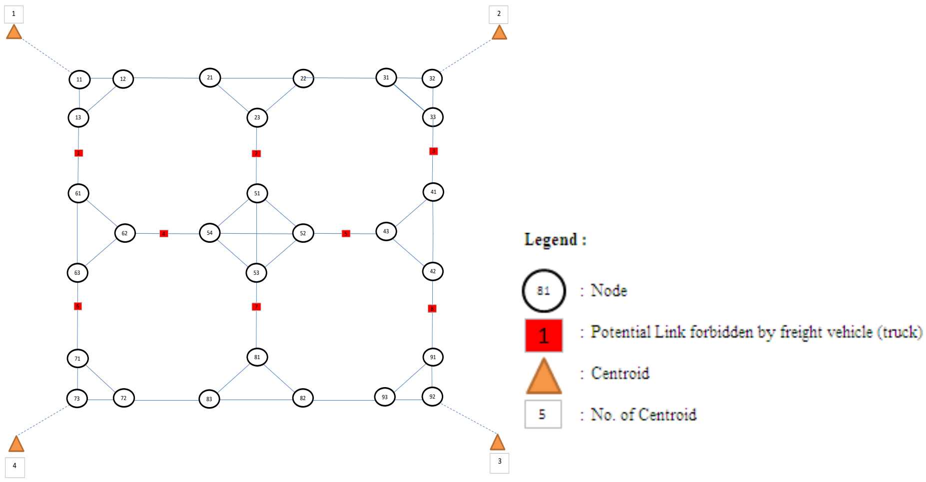


Figure 4. Hypothetical Road Network Model

In Figure 4, it is assumed that the network consists of 12 road connections, 9 intersections, and 4 foci. Representative connections on the connecting road are depicted in Figure 1, and connections at nodes (i.e., intersections) are depicted in Figure 1. Connection numbers: 71-63; 61-13; link numbers 12-21 and 22-31 are assumed to have a high capacity, and link numbers 33-41, 42-91, 93-82, and 83-72 are assumed to have medium capacity. It is assumed that other connections have lower capacity than other connections. Each road link is indicated as having the same length. These assumptions are intended to simplify the validation of model results.

The basic network, the freight vehicle network, and the passenger vehicle (other users) network are the three sections of the network database structure for the urban freight network architecture. The network database includes information on the number of nodes, links, locations of prohibited products (such as trucks) along links, link types, link directions (lanes), lengths of links, link capacities, free flow rates, and other traffic volumes, among other things. intersection types and numbers, cycle times, and green times. Specific network data for freight and passenger vehicles are available regarding forbidden freight locations, trip time for free movement, parameters Ø1 and Ø2, vehicle capacity, VOC, and time value of cargo and passengers.

Table 1. Travel Demand of Freight and Passenger

Origin Zone	Destination Zone	Travel Demand	
		Freight (ton/day)	Passenger (pass/day)
1	2	10.000	15.000
1	3	9.750	14.750
1	4	9.500	14.500
2	1	15.000	35.000
2	3	14.500	34.500
2	4	14.000	34.000
3	1	20.000	30.000
3	2	19.750	29.750
3	4	19.500	29.500
4	1	15.000	25.000
4	2	14.750	24.750
4	3	14.500	24.500

The travel requirements for cargo and passengers are shown in Table 1. In Table 1, there are 4 (four) OD matrices (origin and destination) pairs for each cargo and passenger (daily itinerary). Here it is assumed that a van (truck) can carry 10 tons of cargo at a time, and a passenger car can carry three passengers at a time. Passenger car equivalents for freight and passenger are 2.5 and 1.0, respectively. Allocated travel demand is 10% of peak hours.

Result

The expected result of this paper is to construct a combination of routes for freight vehicle paths from OD pairs, as described in Table 2. Table 2 shows all OD pairs' detailed routing from origin to destination. This combination of routes results from optimizations performed at the upper layers, and the test program can perform optimizations for all possible combinations of connections. At this level, the GLS method can perform infinite path combinations to the solution, resulting in a potential solution of (2^n - 1). All generated combinations are evaluated through a one-shot process over a certain number of iterations, in which case we perform up to 50 iterations.

As mentioned, the scenario was developed by combining road connections that allow heavy goods vehicle (HGV) use and that do not allow trucks due to specific standards. Urban road connections often use this strategy to reduce traffic density (Crainic, 1990b). The letter n in the above Equation represents the link set under consideration. With eight connections, there are 255 scene combinations, and the GLS optimization chooses the best combination for a given iteration and the expected degree of convergence. The specified number of iterations was 50, with a convergence level of up to 0.001. An optimal freight vehicle network is a set of routes (networks) from origin to destination constructed from the scenario that yields the smallest objective function value (see Figure 5).

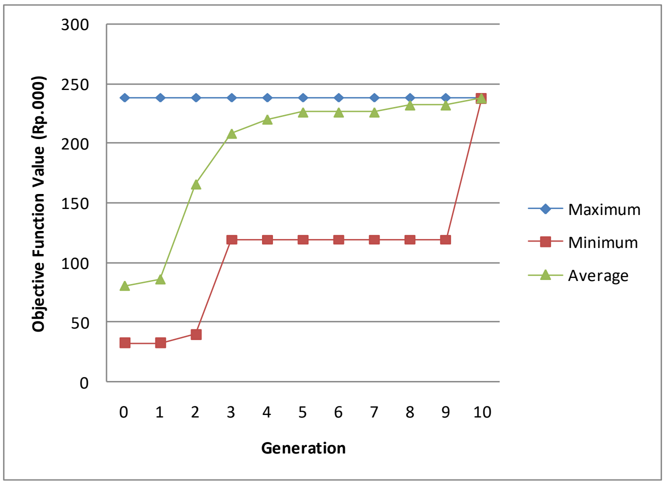


Figure 5. The Convergence of Objective Function Value in Each Generation

Table 2. The Path of Freight Transportation for Each OD Pairs (1th and 2nd zone)

The Path of OD Pairs					
1-2		1-3		1-4	
anode	bnode	anode	bnode	anode	bnode
32	2	92	3	73	4
31	32	91	92	72	73
22	31	93	91	71	72
23	22	82	93	63	71
21	23	81	82	62	63
12	21	53	81	61	62
11	12	54	53	13	61
1	11	52	54	12	13
		51	52	11	12
		23	51	1	11
		21	23		
		12	21		
		11	12		
		1	11		

The Path of OD Pairs					
2-1		2-3		2-4	
anode	bnode	anode	bnode	anode	bnode
11	1	92	3	73	4
12	11	91	92	71	73
21	12	42	91	72	71
23	21	41	42	83	72
22	23	33	41	82	83
31	22	31	33	81	82
32	31	32	31	53	81
2	32	2	32	51	53
				23	51
				22	23
				31	22
				32	31
				2	32

This study conducted experiments on artificial data analyzed by the aforementioned methods. The result converges to the target value of 246,311.9 IDR, as shown in Figure 5. Figure 5 shows that the model satisfies the convergence condition of producing 10 in 0.76 seconds. The GLS combinatorial optimization model shows us the best performance. This is consistent with Yamada et al. GLS methods perform well in solving combinatorial problems.

Table 3. The Path of Freight Transportation for Each OD Pairs (3th and 4th zone)

The Path of OD Pairs					
3-1		3-2		3-4	
anode	bnode	anode	bnode	anode	bnode
11	1	32	2	73	4
12	11	31	32	71	73
21	12	33	31	72	71
22	21	41	33	83	72
23	22	42	41	82	83
51	23	91	42	93	82
52	51	92	91	91	93
53	52	3	92	92	91
81	53			3	92
83	81				
82	83				
93	82				
91	93				
92	91				
3	92				

The Path of OD Pairs					
4-1		4-2		4-3	
anode	bnode	anode	bnode	anode	bnode
11	1	32	2	92	3
13	11	31	32	91	92
61	13	22	31	93	91
63	61	23	22	82	93
71	63	51	23	83	82
73	71	52	51	72	83
4	73	54	52	71	72
		62	54	73	71
		61	62	4	73
		63	61		
		71	63		
		73	71		
		4	73		

CONCLUSION AND FURTHER RESEARCH

The GLS (Genetic Local Search Algorithm) heuristic method can offer a useful set of optimal freight routes in the urban road network system based on the research findings. In a short amount of time, a solution can be discovered by performing iterations to find the optimum fit for the target function. Although this method successfully solved the problem, it may produce different outcomes when applied to a real road network. To increase the model's robustness, it is crucial to conduct a more thorough study of the road traffic network.

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