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Development of Optimization Algorithms for Transportation Problems with Capacity Constraints

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ABSTRACT

Transportation movements in urban areas often compete for road space with other users. Inappropriate selection of transportation routes between origin and destination pairs for goods travel results in increased transportation costs. The main goal for transport operators and road users, other than transport, is to minimize travel costs. This research aims to investigate road sections that can be used for transportation at minimum costs for all origin-destination pairs of goods involved in the road transportation network system to form an optimum transportation network design. The optimization objective is to maximize the difference in total transportation costs of the transportation network system between existing conditions and conditions after optimization. A mathematical model is used to represent road user traffic behavior. The optimization process consists of two stages of activity, referred to as bi-level programming: the lower level and the upper level. The lower level provides information about road user behavior on the road section, as demonstrated in the traffic loading process. The user equilibrium traffic loading with diagonalization is used as the solution technique. The upper level employs the GA-I solution technique, which is a genetic algorithm with additional operators. The research presents a method for optimizing urban transportation networks using GA-I. The method is significantly robust and provides an optimum solution in a short time on a hypothetical network.

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INTRODUCTION

Transportation movements in urban areas often compete for limited road space with other road users, leading to increased traffic congestion. Inefficient selection of transportation routes between origin and destination pairs for goods transportation can result in higher transportation costs, negatively impacting goods transport operators. However, all road users share the common goal of minimizing travel costs, regardless of their mode of transportation. This research aims to identify road sections that can be used for transportation at the lowest possible cost for all origin-destination pairs of goods within the road transportation network system. The ultimate objective is to develop an optimal transportation network design.

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The selection of road segments for transportation network design is a combinatorial problem. This research develops a mathematical model to represent traffic behavior and optimize the difference in total transportation costs between conditions with and without optimization. The optimization process consists of two stages of activity, known as bi-level programming.

For a long time, the concept of a bi-level programming model in decision making has been growing, and this concept can be implemented in the process of determining urban transportation routes. Taniguchi and Thomson (2003) introduced the notion of city logistics in a bi-level framework in the context of urban transportation, although the conduct of freight carriers has not been influenced by the behavior of non-goods (passenger) traffic.

Bi-level programming involves the programming of the behavior of the decision makers to determine the optimal transportation trajectory. This trajectory is composed of a lower level and an upper level. The lower level considers the representation of freight carrier behavior and/or non-freight traffic to model field reality in a modeling framework. The upper level programming represents the behavior of policy makers with certain objectives and analytical methods.

At the lower level, freight carriers choose routes based on System Optimum (SO) and User Equilibrium (UE). The search for transport routes using the Optimum System can be performed under static traffic conditions. In this case, the link costs such as distance, time, or cost are assumed to be fixed. The Optimum System allows for route selection in dynamic traffic, where link costs are influenced by total traffic movements and road capacity limitations.

The language used is clear, objective, and value-neutral, with a formal register and precise word choice. The text adheres to conventional structure and formatting features, including consistent citation and footnote style. The sentences and paragraphs create a logical flow of information with causal connections between statements. There are no spelling, grammar, or syntax problems in the text.. No changes have been made to the content as instructed. This can be achieved through the use of real-time data or by simulating vehicle traffic with UE system optimization, which is commonly used in urban areas. Taniguchi et al. developed transportation routing with static traffic, while Frazilla et al. (2005), Yamada et al. (2010), and Taniguchi et al. (2007) developed transportation routing influenced by dynamic traffic. Additionally, Frazilla et al. considered multimodal/multiuser aspects in the goods transport network optimization process at a lower level.

At the higher level, policy makers' behavior is represented by methods for determining transportation trajectories with specific objectives. In 2009, Taniguchi et al. improved the objectivity of vehicle route selection models at the upper level by considering the impact of air pollution, specifically NOx, and utilizing bi-level programming principles outlined in the multi-agent concept. They developed the best route selection method using the Genetic Algorithm. Frazilla (2005) and Sofyan et al. (2010) also developed the Genetic Algorithm method for selecting transportation routes. Restricting large goods trucks from entering urban areas can be a mechanism for selecting transportation routes. This policy is applicable to urban areas because medium and large trucks are the largest contributors to NOx and PM emissions per unit of time along the length of the road. Castro et al. (2009) have reviewed this method, but route selection is still done manually.

In the context of bi-level programming, the upper level can be viewed as a combinatorial optimization problem. To solve such problems, there are three types of methods: strict, approximate, and metaheuristic. In recent years, several metaheuristic procedures have been developed and applied in soft computing environments. The technique plays a vital role in solving complex mathematical programming problems, particularly those involving difficult network problems (NP-hard problems). While it cannot guarantee exact optimal solutions, it can provide practical and reasonable results. As a result, it is commonly used for combinatorial optimization problems where determining an exact optimal solution is challenging.

Ribeiro and Hansen (2001) provide an excellent introduction to the basic concepts of metaheuristics. Genetic Algorithms (GA), tabu search, simulated annealing, and ant colony optimization are typical solution techniques in metaheuristics. Among these techniques, Genetic Algorithms are the most frequently used and developed in various variants due to their reliability in solving problems. However, it is possible that other metaheuristic solution techniques may provide better results.

The Genetic Algorithm is a metaheuristic method introduced by Holland (1979) based on the mechanisms of natural selection and genetics. Possible solutions are constructed from individuals known as chromosomes, with each position in a chromosome being referred to as a gene and the gene value as the allelic value. The most common allelic value is the binary value of {0,1}. A population is formed by a number of individuals who have the opportunity to be selected to become a solution. The local search method uses a fitness function to determine which of the individuals in the population have the potential to become a solution.

The local search method uses a fitness function to evaluate the remaining capacity of each population of chromosomes and employs simple operators such as selection, reproduction, and mutation to create a new set of artificial populations. Goldberg (1989) has discussed some applications of GA in optimization problems. GA has also been widely applied in the field of transportation. Cantarella and Vitetta (1994) employed genetic algorithms in multi-level programming to address network design and urban parking problems. At a broader level, genetic procedures are used to evaluate new network configurations.

This process involves calculating signal settings, network delays, and transient flows until two successive traffic flow patterns are controlled within a tolerance. The language used is clear, objective, and value-neutral, with a formal register and precise word choice. The text adheres to conventional structural and formatting conventions, including a consistent citation and footnote style. The structure is logical and balanced, with causal relationships between statements. There are no spelling, grammar, or syntax problems in the text.. No content changes have been made. In 1993, as an improved version of GA for transportation network design, Xiong and Schneider introduced the Cumulative Genetic

Algorithm (CGA). CGA stores all population members with high fitness values and uses them along with new population members for reproduction.

In addition, neural network analysis is used to generate a set of individuals that are different from the previous generation (parents). Kwan and Wren (1994) proposed a hybrid GA for the bus driver scheduling problem. The approach combines GA with a rule based on driver task estimation and integer programming. GA is used to produce the best population, followed by integer programming to develop optimal driver scheduling. Yamada et al. (1999) used a GA approach to determine the optimal size and location of logistics terminals. The algorithm's performance is improved by including high-end operators. This operator preserves the best-performing individuals in a population, such as chromosomes with a high fitness function, for the next generation to use. Additional model development involves multi-objective analysis, which is referred to as the Vector Evaluation Genetic Algorithm (VEGA) by Frazilla (2005).

METHODS

As mentioned earlier, the framework of this paper for designing urban transportation networks is based on two-level programming, specifically bi-level programming. The bi-level framework consists of upper level and lower level problems. The upper level problems include the formulation of objective functions and optimization techniques, while the lower level problems include the traffic behavior of transport users and types of non-transport users in the road network system. The objective of this research paper is to achieve the optimal total network costs. This goal is integrated into the proposed solution technique at the upper level.

Lower Level Problems

a. Road Network Representation

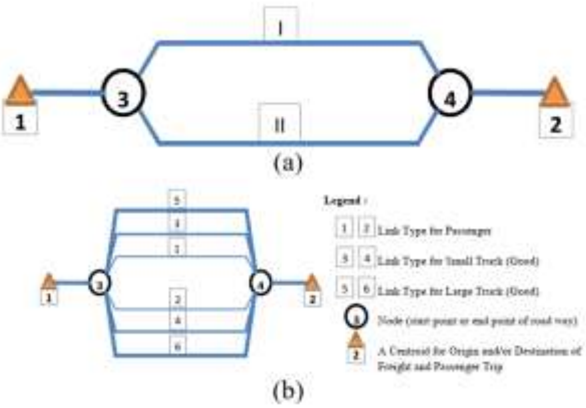

Figure 1. Road transportation network representation

The road network system is often portrayed as a link of interconnected road sections that connect the origin and destination pairs of travel. Figure 1 depicts a basic road network connecting two travel origins and destinations. The road network (Figure 1.a) consists of two road segments that connect two nodes (nodes 3 and 4). These two road segments

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may be the best option for the origin (1) and destination (2) zones. Each road stretch is designed to be passable by freight vehicles and other vehicles. The road section is exploited in modeling such that it appears to be divided into road connection links based on the type of users who can pass through it (Figure 1.b).

Each road segment can accommodate three types of vehicles: passenger cars, small trucks, and large trucks in this network model example. Links 1 and 2 represent the link types for passenger cars. Links 3 and 4 represent the link types for small truck users, and links 5 and 6 represent the link types for large truck users. The abstract network model G(N,A) defines the network representation, where N is a node collection and A is a link collection.

Nodes 3 and 4 represent intersections. In urban road networks, delay at intersections is a critical component and must be fully considered. Figure 2 illustrates the representation of vehicle movements. Intersection delay depends on vehicle operating characteristics, traffic flow, and intersection capacity.

According to the form of control studied in this study, there are two categories of intersections: signalized and priority intersections. The link representation in the network system is expressed as a set of links A based on the abstract road network representation, which consists of road link links (Aj), left turn links at signalized intersections (Aski), continuous links at signalized intersections (Asl), and right turn links at intersections. Left turn link at priority junctions (Apki), continuous link at priority intersections (Apl), and right turn link at priority intersections (Apka) are all signalized. Centroid connectors are also regarded abstract linkages in the network architecture, bridging the journey origin and destination zones (Ac).

$$A = A_j \cup A_{ski} \cup A_{sl} \cup A_{ska} \cup A_{pki} \cup A_{pl}\ A_{pka} \cup A_c.$$

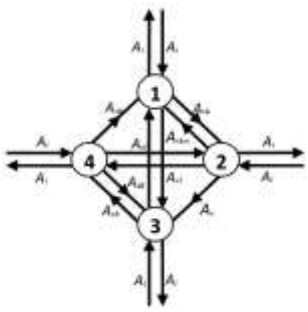

Figure 2. Traffic flow at a crossroads is depicted.

The type of intersection control, intersection geometry, and traffic flow characteristics affect the delay time at each intersection approach. Calculating delay times differs between signalized and priority intersections, particularly in determining intersection capacity. For signalized crossings, the crossing capacity is defined by the allocation of green time on each approach, while for priority crossings, the crossing capacity is defined by the crossing type and lateral obstructions. Intersection delay times are formulated based on the method developed in MKJI, 1997.

b. Link Cost Function

One of the limits for a vehicle passing through a road link is the expense of the link. The expenses spent by user type i on a link an are expressed as generalized costs that include tariff components and travel time charges (see equation 1). The time cost component is calculated by multiplying the journey time (delay time plus free time) by the time value for each user type.

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

Equation 1

Where:

ρ_a^i = price for user type i on link a (Rp/km)

α^i = time value for user type i (Rp/hour)

$d_a^i(x_a^i)$ = travel time of user type i on link a (hours)

The fare component is a fixed number that does not change with traffic volume, whereas the time cost component is a function of time and traffic volume, the value of which varies depending on the link type. The link types for goods and non-goods (passenger) vehicles are distinguished in this situation. Furthermore, to prevent complexity or non-singularity solutions, these two types of links are described in a polynomial estimation formulation (see equation 2) for traffic loading in transportation modeling.

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

Equation 2

x_a^T = Total traffic flow on link a (pcu/hour)

r_a^T = capacity on link a (pcu/hour)

ϕ_1, ϕ_2, γ = Calibrated parameters

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

c. Solution Engineering

This research considers goods and passengers as multiclass users, performs modal separation and route selection simultaneously, and transforms multimodal network into unimodal abstract mode network. Thus, the corresponding UE problem is an inseparable asymmetric Jacobian matrix cost function between user types. This is a variational inequality problem.

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The multimodal load problem can be simplified to a single mode load with different link types, assuming that the marginal cost of using a particular mode is inelastic to the volume shared with other modes. Since there is more than one assigned user, this case can be considered a multi-class user equilibrium assignment problem with an inseparable and asymmetric cost function. The asymmetry occurs because the first derivative of the cost function differs between users, namely goods and passengers.

Upper Level Problems

a. Formulation of Objective Functions

For instance, in a basic road network (as shown in Figure 4), road links are expressed as a subset of A, where A = A1 ∪ A2 ∪ A3. Here, A1 = {a: a = 1, 2, ..., n} is defined as the set of existing unmodified links, A2 = {a: a = n+1, n+2, ..., n+m} is the existing link set that allows for an action (scenario) to be implemented, and A3 = {a: a = n+m+1, ..., n+2m} is the updated version of set A2 (after the action has been implemented). Links in A2 and A3 are numbered so that if a value from A2 is selected, the corresponding treatment will be implemented. Link a+m in A3 will replace a if it is selected, otherwise it will be discarded.

Following that, we define the set of possible action combinations, y, associated with A3 (or A2), as y =yaa = n+m+1,n+2m, (or y =ya a = n+1,n+m), where yes is an action implementation indicator with a binary value of 1 if the action corresponding to link an in set A2 is implemented, and 0 otherwise.

In higher level problems, the objective function is based on the difference between the total generalized cost of existing conditions and the total generalized cost after performing the action. This is a simplified version of economic feasibility that reflects an action's economic efficacy. This parameter helps assess the relative improvement (in comparison to the beginning state) of a set of actions.

The objective function for selecting a combination of actions will maximize the value of the difference in total generalized costs of goods and non-goods transportation by denoting x^{i*}_{oa} as the equilibrium link flow for user type i on the initial link, cia as the generalized link cost function on link a, and F as the set/set of types of transport users goods and non-goods user types. The following is the definition of the objective function f(y):

$$Max\ f(y)=\sum_{i\in F}\left[\sum_{a\in A_1\cup A_2} x^{i*}_{0a}c^i_a(x^{i*}_{0a})-\left(\sum_{a\in A_1} x^{i*}_a c^i_a(x^{i*}_a)+\sum_{a\in A_2} x^{i*}_a c^i_a(x^{i*}_a, y_a)\right)\right]$$

x_a^{i*} : Each type of user has a link flow that is a solution to UE problems by implementing a mix of activities (pcu/hour).

$c_a^i(x_a^{i*}, y_a)$: generalized cost on link a according to user type i which depends on the equilibrium flow and whether the action is implemented or not (action implementation indicator yes) (Rp)

b. Solution Techniques

Procedures based on genetic algorithms (GA) are utilized to solve problems at the highest level. GA has been extensively employed to provide approximate optimal solutions in various practical applications. Approximate solutions can be obtained through genetic operators, such as generation, reproduction (selection), crossover, and mutation. The Simple Genetic Algorithm (SGA) initiates the process by generating a population that represents a group of

individuals who include possible solutions to the problem being analyzed. The population of the next generation is determined through a procedure that involves selecting parents and producing new individuals based on the characteristics of the parents' preparation. SGA was developed and modified by altering the basic characteristics of parent preparation. Specifically, a number of elite individuals (those with the highest fitness value) were retained to later become members of the parent population for reproduction. This study tested a solution procedure based on Genetic Algorithm improved with additive (GA-I) type.

In general, the GA technique is as follows: in the initial generation, a set of actions with a fixed number (ie: a fixed number of individuals) is formed, and the chromosomes are generated at random. The objective function value provided by equation (3). After that, for each individual, the fitness value is calculated. The technique is outlined schematically below. SGA is a simplified form of the GA scheme that uses normal reproduction, crossover, and mutation operators. In this scenario, linear fitness scaling is used in the reproduction process, as well as single point crossover and creep mutation. Elite persons are chosen in order to keep some of the top individuals for the following generation. The mutation mechanism is the same as in SGA, however uniform crossover (shown in Figure 3) is used in the crossover process. This procedure's algorithm is as follows:

1. Initialization - Create an initial population (a collection of random strings) and set the number of generations (g) to zero.
2. Fitness calculation - Determine each individual's fitness value in the population.
3. Retaining Elite Individuals - Identify a group of people (i.e. an elite number to keep) who have the greatest fitness values.

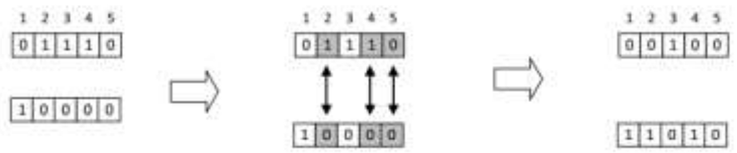

Figure 3. Uniform Crossover Operator

4. Evolution - reproduce - do a uniform crossover (uniform) - do a creeping mutation (creep mutation) - set g = g + 1
5. Elite Individual Insertion and Repetition - Incorporate the elite individuals from Step 3 into the new population.
   - If the halting condition is met, calculate the fitness of the previous generation and stop. If not, return to Step 2.

RESULT DAN DISCUSSION

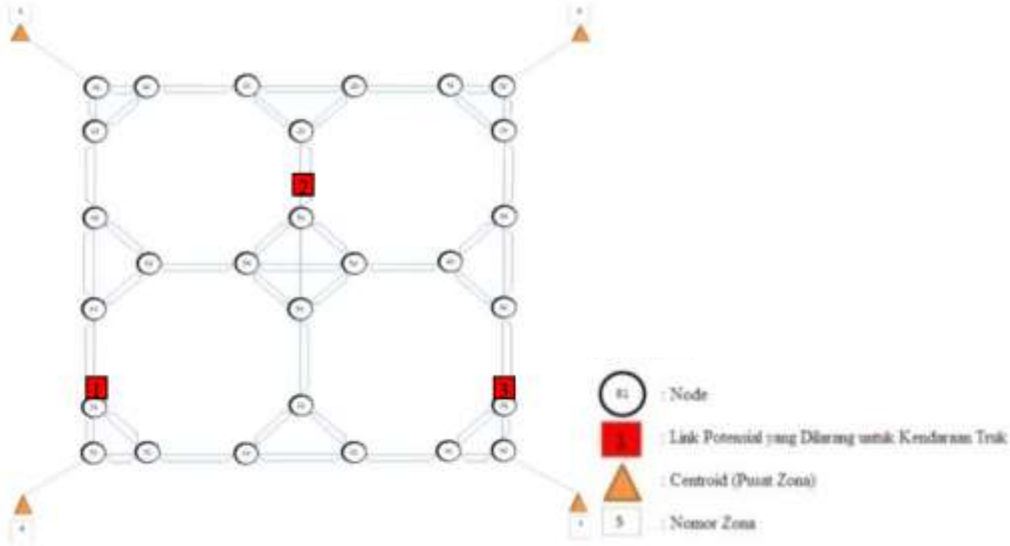

Figure 4. Representation of a hypothetical road network differentiated by transportation and non-freight links and 3 (three) alternative groups of potential road segments opened/closed.

The performance of the model under development was assessed by testing the GA-I approach on a basic hypothetical transport network (Figure 4). The network consists of 12 road segments, 9 nodes (junctions), and 4 pairs of origin destinations for commodities and passengers. There are three road portions with the potential to restrict truck traffic (open and close connection), referred to as alternative road sections. Of the three possible road segments, The process involves developing 7 (23-1) road segment combinations, which are then analyzed using the GA-I procedure, as illustrated in Figure 4 and Table 1. This option is one of the transportation management strategies commonly used in urban areas.

Tabel 1. Alternative road sections to open/close

No.	Segment Alternative Group	Alternative Section Links that Potentially are opened/closed
1.	1	63 – 71 & 71 – 63
2.	2	23 – 51 & 51 – 23
3.	3	42 – 91 & 91 – 42

The model was deemed robust after undergoing a robustness test process, specifically the robustness model. To test the robustness of the traffic loading model with GA-I optimization, the initial parameter values for the genetic operators were determined based on previous research findings (e.g. Goldberg, 1989; Taniguchi et al., 1999; Yamada et al., 1999). The chromosome length is 3, representing the group of segments that are alternative actions. The crossover rate is set at 0.6, and the mutation rate is 0.03. In each generation, one elite is maintained.

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To test the robustness of the GA-I optimization model, various combinations of GA parameters were used, including the initial random number (random seed), the number of individuals in one generation (pop size), and the number of generations in one test process. A model is considered robust if it consistently shows the same solution indicators when tested with various combinations of GA parameters, specifically a consistent objective function.

The initial random number tested ranges from 1 to 20, the population size in one generation ranges from 5 to 45 with an interval of 5, and the number of generations tested ranges from 5 to 50 with an interval of 5. The GA was tested against the model with 1800 parameter combinations.

The test results indicate that the GA-I optimization model with diagonalization loading is robust, as it achieves the same optimum objective function for each random initial number tested. However, the achievement of the optimum objective function value occurs at different combinations of pop size parameters and number of generations, which differentiates the model's robustness to various random initial numbers.

Tabel 2. In hypothetical transportation network optimization, program performance in reaching optimal objective function values

Seed Random	Pop Size								
	5	10	15	20	25	30	35	40	45
	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

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Information:
Popsize : number of individuals in 1 (one) generation
Genes : number of generations in 1 simulation
Seed Random : random initial number

Table 2 presents the results of the model tests using various GA parameter values. Testing fewer parameter combinations reduces the time required for each test, while testing more combinations does not necessarily lead to a faster attainment of the optimum objective function value. Selecting a combination of GA parameters that will be used as GA parameter values for model applications in real networks requires achieving the speed of emergence of the optimum objective function value.

Table 2 shows the test results, indicating the speed at which the optimum objective function value appears for each parameter combination. The combination of a population size of 5, 5 generations, and random seeds 9, 12, and 17 resulted in the fastest attainment of the optimum objective function value.

Frazila (2005) suggests that the length of the chromosome being tested also affects the achievement of the optimum objective function value. In real network conditions, the number of chromosomes representing alternative actions is typically greater than three. Therefore, the speed at which the optimum objective function value emerges in this trial does not guarantee the same results in a real network. It is necessary to select parameter combinations using the current test results as a reference. In statistical terms, larger populations have a lower probability of producing a specific value, but a greater probability of producing the expected value. Therefore, when applying this to a real network, it is important to select the parameter combination that provides the greatest chance of producing the desired value.Therefore, when applying this to a real network, it is important to select the parameter combination that provides the greatest chance of producing the desired value. Figure 5 below shows the performance of the GA-I method for a randomly selected initial number combination of 9.

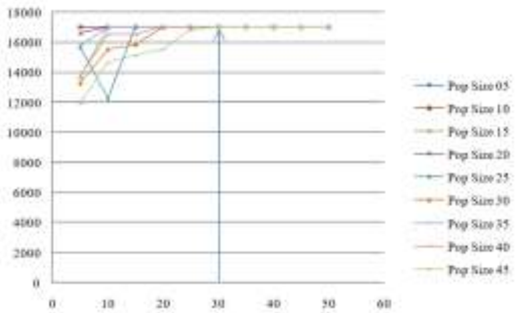

Figure 5. Depicts the effect of population size and generation on the convergence of the objective function value.

The figure above shows that in the model test simulation with an initial random number of 9, convergence for all population sizes (pop size) begins at the 30th generation. Pop size 10 reaches convergence with the smallest number of generations, beginning at the 5th generation. The population size that reaches convergence with the largest number of generations is pop size 15, which begins to reach convergence at the number of generations 30. To save simulation time on real networks, it is necessary to determine the number of generations and number of individuals. This is because the larger the population size and number of generations, the longer the time required for optimization simulations.

Based on the results of the robustness test of the model, the GA-I optimization method and diagonalization loading were used to optimize a hypothetical goods network. The optimization resulted in the closure of road sections 1 and 2 (chromosome 110), which provided an optimum objective function of IDR 17,002,000.13. Road section group 1 includes the closure of links 63-71 and 71-63, while road section group 2 includes the closure of links 23-51 and 51-23.

CONCLUSION

It can be concluded that the proposed model is highly robust based on the model testing results. The model has been optimized with genetic parameters, including a population size of 5, 5 individuals, a crossover rate of 0.6, and a mutation rate of 0.03. Depending on the size of the network and the number of alternative road segments, the number of populations and individuals needed to optimize will vary. It is necessary to re-examine the effective and efficient number of populations and individuals to apply the model to larger networks. The decision to open or close road sections is effective in providing optimal transportation network design solutions. The GA optimization technique is effective in producing an efficient transportation network scheme, as indicated by the lower optimum objective function value compared to existing conditions. The GA method is a reliable way to find the optimum solution. It can reduce the amount of repetitive work required, particularly when creating scenario combinations. This heuristic optimization method is especially effective for combinatorial problems with many possible actions/scenarios (2n-1, where n = alternative scenarios). The development of GA-I in this research, as compared to its predecessor Simple Genetic Algorithm (SGA), demonstrates that optimization models using GA-I can be an effective alternative for optimizing transport network design, particularly for freight transport.

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