

Generative Methods for Planning Public Transportation Systems

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Abstract. This paper considers a method for generating new bus routes to optimize the transport connectivity of an area and the average travel time, based on the use of a genetic algorithm on the intermodal graph of public transport. This method is intended to identify the potential of the transport system and routes for development by assessing and optimizing the integral accessibility and connectivity of the area. For this purpose, data on city blocks are collected and assembled into a network model. The calculation of public transport travel time between blocks is done using an intermodal graph. The result of the work is a new network of optimal bus routes proposed by the algorithm. The proposed method makes it possible to model on available open data the changes of the public transport system for further development with change assessment.

Keywords: Public transport · Network model · Transport connectivity · Generative approach · Genetic algorithm

1 Introduction

One of the key components of a city is transport system, which can be defined as a complex network of interconnected elements designed to facilitate the movement of people and goods. In assessing the quality of life in cities, it is important to consider the presence of efficient and well-planned public transport networks, which play an important role in ensuring sustainable urban development and addressing the challenges of urbanization.

Important indicators for assessing the performance of transport in a city can be the transport accessibility and connectivity of territories. Transportation accessibility affects several aspects of citizens' lives. For example, increased supply affects the active lifestyles of citizens, as low-income groups or those who use private transportation may be more likely to walk to bus stops [1]. Also, better provision of transportation increases employment in certain neighborhoods. In addition, lack of mobility can cause social exclusion, whereby people are excluded from participating in the economic, political and social life of the community [2,3]. To improve these indicators, optimization of the public transport system is necessary.

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Addressing the optimization of public transport system is not just important; it is a pressing necessity in the current urban landscape. With the ongoing challenges of population growth and increased urbanization, the strain on existing public transport networks continues to escalate. Overcoming the reluctance of individuals to utilize public transport is crucial for the sustainable development of urban areas. The issues of overcrowded vehicles, inconvenient schedules, and slow speeds contribute to this reluctance, highlighting the immediate need for a solution [4]. Delays in resolving these challenges can exacerbate environmental issues, such as air pollution and traffic congestion, further impacting the overall quality of urban life.

Optimizing public transport systems can motivate people to switch from private cars to public transport, minimizing environmental damage from air pollution and reducing traffic. Existing methods of optimization and planning of public transport routes usually consider total costs, which include time costs. However, such modeling is resource-intensive both in terms of computational power and availability of the necessary data.

Urban planners also rely on transportation connectivity and average travel time to analyze transportation infrastructure, when making decisions about urban spatial development [5]. Depending on the objectives, the transport connectivity of urban areas can be defined differently. In this paper, connectivity is inseparable from accessibility, it reflects how different parts of a city or area are connected through the time cost of travel.

The purpose of this study is to develop a generative method for planning and optimizing public transportation systems by generating new transportation routes based on existing ones using a genetic algorithm. The optimality criterion is the average travel time, which is calculated from the connectivity matrix of a given area. The proposed method is designed to determine the potential of the public transport system and routes for development. Since full-scale transport modeling is long and expensive, and sometimes it is not clear whether it is time and whether it is worth doing. Therefore, a method is needed to assess whether it makes sense to invest in large-scale transformations or not.

2 Related Works

2.1 Optimization of Transport Systems

In the main problems of transport assessment in cities, the object under consideration is the transport system or transport model. The city transport model is a mathematical and computational representation of the system of transportation and traffic in the city [6]. It is intended for analysis, forecasting and optimization of transport infrastructure and traffic in the city.

The goal of transport system optimization is to enhance the overall functionality and effectiveness of transportation services. The resulting transport system should achieve several key objectives [7]:

– efficient resource utilization;

– minimized travel time;
– adaptability to passenger demand;
– enhanced accessibility;
– costs reduction;
– improved connectivity;
– enhanced customer experience;
– equitable distribution of services.

There are many approaches to describe transportation systems, including flow modeling to find optimal states. According to the level of detail, they can be divided into several groups: macroscopic, microscopic and mesoscopic [8]. Macroscopic methods include those that treat the flow of vehicles as an indivisible unit. These include peer models, the system dynamics model and traditional four-step transportation models [9]. Among the disadvantages of this type of models are their relative inaccuracy and static results with high calculation speed and low requirements for computational resources.

Microscopic models describe the behavior of individual flow participants and their interactions. Microscopic methods include agent-based modeling [6] known as multi-agent simulations for transportation networks [10]. Methods of this type require extensive input data and large computing power, but the results obtained are characterized by high accuracy. Mesoscopic methods combine the above approaches describing the behavior of individual agents and considering their behavior at the macroscopic level. An example of such a method is the gravity model and entropy model [11]. This type of model is often used in public transportation route planning problems. Despite their comparative compactness, mesoscopic models have disadvantages in the form of a small number of parameters for tuning and limited application.

Transportation demand modeling is an important component of transportation models. It can be done by several methods, including real-time traffic demand modeling and the use of mobile data [12–14].

A logical extension of the transportation demand modeling task is the problem of planning and optimization of public transport routes, commonly known as the transportation routing problem. Representing a variation of the traveling salesman problem, it is an NP-hard problem whose solution can be approximated using combinatorial optimization algorithms.

To solve this problem the method of branches and bounds can be used, but only with a small number of vertices it is effective if a transportation network is represented as a graph. Approximate metaheuristic approaches were used to solve the transportation routing problem [15]. Also, the papers mention the use of graphical methods and nomograms that demonstrate less efficiency [16]. Passenger flow density, total time spent by passengers, number of transfers, costs of transport organizations can be chosen as an optimality criterion.

2.2 Public Transport Routes Planning

The organization of an urban public transport system is based on the following input parameters: public demand, geographical characteristics, available

transport quantity [17]. The objective is to create a set of routes and associated schedules and to allocate transportation units to these routes.

A more detailed route planning problem is to design a network of public transport stops and lines covering the maximum area, prioritizing direct trips with the shortest distances and minimizing the number of routes and their total length [18]. The solution to the problem is based on the processing of data on the existing road network, potential bus stop locations and transfer zones, the location of parking lots and public transportation service areas [19].

To identify the network of routes that best satisfy public demand, origin-destination (OD) matrices are used to describe the relationship between passengers' origin and destination points and reflect various parameters, such as the travel time spent between these points or the value of demand for such a route obtained through surveys or big data technologies [13,20].

There are several approaches to solve the transportation network design problem, detailed in survey papers [17,21,22]. The mathematical approach aims to find the best solution based on certain criteria such as minimizing travel time, route length [23], number of stops [24] and operating costs, maximizing coverage area. Since mathematical methods aim at finding the best solution, they require high time and computational resources.

Heuristic methods solve this problem by offering not the best but a "near-optimal" solution. They can be used to sequentially remove routes of a fully connected network, or to sequentially add them to an initially empty network [25].

According to the researches [26–28] traditional methods were replaced by generative metaheuristic methods (GA, SA, ASO). This shift is explained by the complexity of the problem, which can be described as NP-hard.

Generative approaches use automated processes to create numerous designs to address a specific problem, continuing until predefined conditions are met. The generative design offers significant advantages over traditional workflows, with a diversity of outputs being a standout feature [29]. It excels, especially in tackling complex, high-dimensional solution spaces that are often encountered in multi-objective and multi-criteria design problems. By incorporating objectives and constraints into the alternative generation or evaluation processes, the generative design enables the effective resolution of multifaceted problems with reasonable computational efforts and results.

Genetic algorithm is used as one the base of the scaled-down transport system [30]. The instance dataset is created by scaling down the street network as well as transforming pre-existing routes to fit it. This methodology is applied to Nottingham, UK, to create a benchmark dataset for bus route optimization. The paper employs a genetic algorithm tailored for restricted route start and end points. The optimization results are compared with actual bus routes in Nottingham, demonstrating the potential of this network design method for improving public transport systems. When a non-dominated sorted genetic algorithm is used, the initial population is randomly generated, focusing on demand satisfaction with the lowest transfer rate possible [31]. Genetic algorithms are

widely used to optimize public transport route networks in agent-based models [32,33].

3 Method for Generating Public Transportation Routes

The objective of this paper is to develop a method for generating new public transport routes to optimize the transport connectivity of an area and the average travel time using open data. The optimization model is represented by the formula 1. This approach, despite its importance, has not been widely adopted in the existing literature.

$$\mathbf{mean}(C) = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} \rightarrow \min \tag{1}$$

where

- C - connectivity matrix;
- n - number of zones in the selected territory;
- c_{ij} - travel time between zones of origin i and destination j.

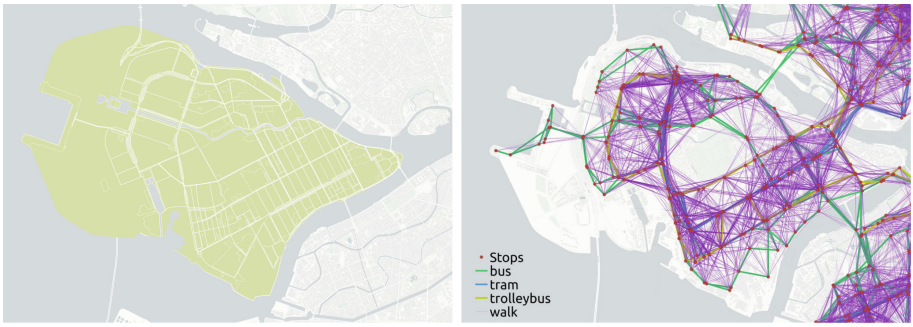
The planning of potential public transport routes involves complex transport modeling that requires a large amount of data and computational power to assess the effects of potential transformations on the territory. The proposed method allows generating a new route and/or modify an existing one and see how it affects the accessibility of an area, using open available data.

Transport connectivity refers to the mutual transport accessibility of urban areas. Optimizing connectivity between city blocks holds paramount importance for several reasons. Firstly, efficient inter-blocks connectivity is instrumental in fostering economic growth and development by facilitating the seamless movement of goods, services, and human resources. A well-optimized network ensures that various city districts are interconnected, promoting accessibility and reducing transportation barriers. Secondly, optimizing connectivity enhances overall urban mobility, providing residents with reliable and convenient transportation options. This, in turn, contributes to improved quality of life, reduced travel times, and increased accessibility to essential services and amenities across different areas.

All computations are performed on a block-network model of the city [34], a simplified representation of the city to speed up the calculation of various indicators. The model is assembled using the BlocksNet library [35] and represents a set of city blocks in a given area, which are connected by paths calculated using an intermodal graph of public transport [36]. The method was tested on the territory of Vasilievsky Island, St. Petersburg, Russia's second most populous city.

3.1 Data

To model a given area and its public transportation, open data from OpenStreetMap are used [37], which are automatically collected using modules in the BlocksNet library. Using the urban blocks generation method, a geo-layer with blocks, the minimum spatial unit for urban environment evaluation, is obtained. The result is presented in Fig. 1a.



(a) Geolayer with blocks (b) Intermodal public transport graph

Fig. 1. Input data

An intermodal graph is collected for transportation assessment. The edges of this graph are the pedestrian ways, and public transport routes are the nodes are the points of connection between the pedestrian sections and public transport stops (Fig. 1b). The graph contains the routes of buses, trams and trolleybuses. Travel delays due to traffic congestion are not considered in the graph. Each mode of public transport in the intermodal graph along the edge without taking into account traffic jams with a fixed averaged speed, which was taken from the estimation of the developers of this graph [36].

As an optimality criterion, we propose a value of the average block connectivity of a city or given area [5], obtained using the BlocksNet library and representing the average travel time between all possible pairs of city blocks using all available travel modes. Bus routes were taken for optimization. To evaluate the performance of the bus route system, we developed a fitness function that calculates the average blocks connectivity by combining a modified bus route with an unchanged part of the original intermodal graph containing information about other types of transportation and unchanged bus routes.

3.2 Description of the Optimization Method

Bus network modification consists of sequential route optimization, which involves removal and addition of new direct routes (edges) between pairs of existing stops (nodes) during the genetic algorithm, which will be described below.

The modified routes are later combined into a common new intermodal graph (Fig. 2).

The graph of the street-road network is used to obtain travel time information on the new edges. The transport speed for new edges to the optimized graph is taken to be the same as in the initial intermodal graph described above. If a pair of stops is not directly connected by an edge, the vertices of the street-road network graph that are closest to the ones under consideration are found, and the shortest travel time is found using Dijkstra's algorithm and summing the weights of the found edges. Figure 3 shows the mutual layout of bus stops and nodes of the street-road network graph used to create new edges. To make the genetic algorithm work quickly, the fully connected graph of all possible connections between bus stops can be calculated in advance if the area under consideration is small.

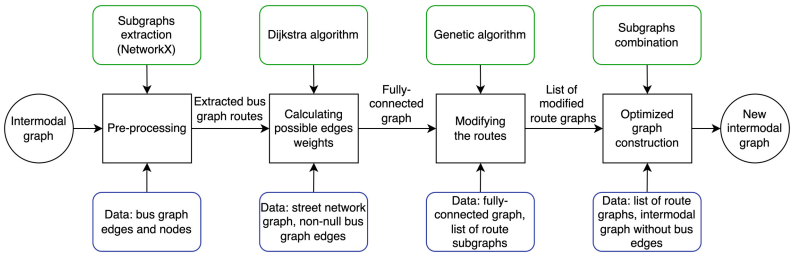


Fig. 2. Optimization algorithm block diagram

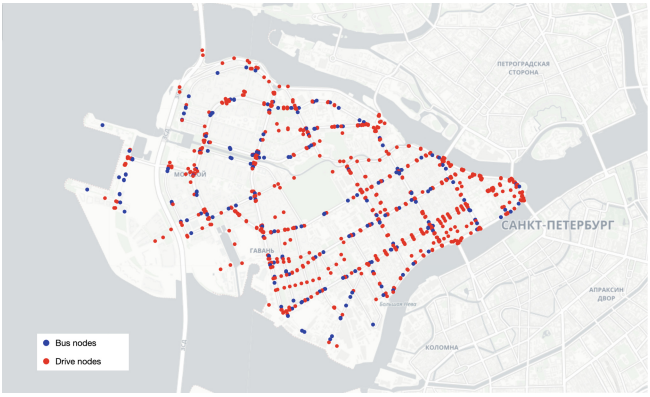


Fig. 3. Mutual location of bus stops and nodes of the street-road network graph

A genetic algorithm (GA) was chosen as a generative method, obtaining an optimal solution from the initial one over several iterations. Possible solutions

(instances of the modified bus route graph) are represented as individuals subject to iterations (eras) of evolution. As the initial population for the algorithm, N modifications of the existing bus route are generated, obtained by replacing a random edge with a pair of edges, containing a new bus stop.

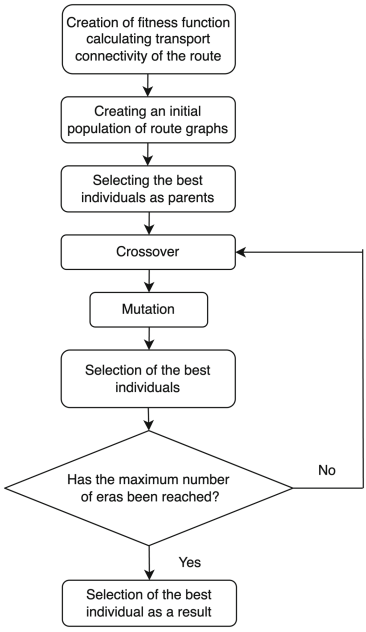


Fig. 4. Genetic algorithm block diagram

For each individual, the value of the fitness function is calculated, and 50% of individuals are selected as parents to create offspring using a tournament selection algorithm. Each pair of parents is formed from the best individuals from two random subsets of the initial population of a given size T.

After selecting pairs of parent individuals, the crossover is carried out between them: a list of edges of a parent is created, after which a random separator index is selected, according to which both lists are divided into two parts, which form a new pair of individuals after recombination.

With probability p, mutation is applied to each individual: random removal and addition of new edges, as described above. The routes obtained are combined with the initial population, and among them, the fittest ones are selected based on the value of the fitness function. If the condition for stopping the algorithm (a given number of iterations k) is not reached, a new era of choosing pairs of parents, crossing and mutation is started. The result of applying the algorithm is an individual with the best value of the fitness function (Fig. 4).

4 Experiments

4.1 Single Route Optimization

To test the method, the genetic algorithm was applied to a single bus route №220 in a given area (Fig. 5a). In different experiments, the route modification options may vary due to the stochastic nature of the generation algorithm. Figure 5b shows the modified route. As can be seen, the new route makes two "duplications" - it drives to stops that are close to other stops on its route.

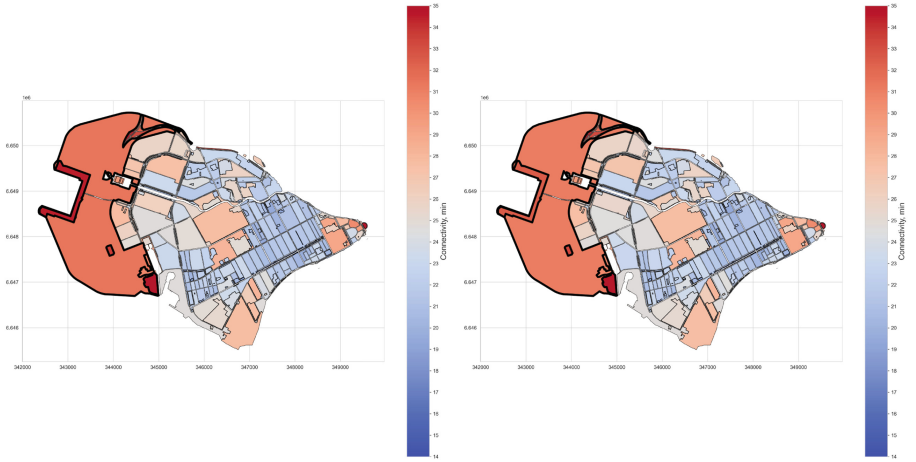


(a) Initial bus route 220



(b) Modified bus route 220

Fig. 5. Single bus route before and after GA application



(a) Before (b) After

Fig. 6. Transport connectivity before and after GA application on the single route

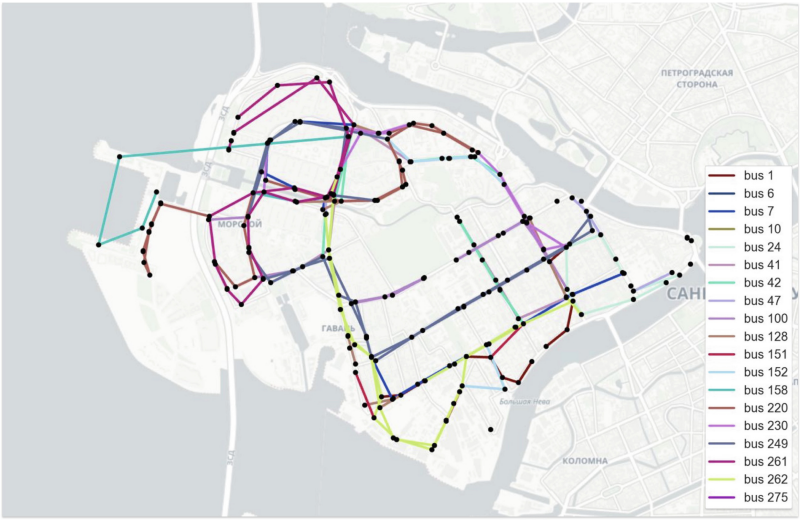
Figure 6 shows the transport connectivity of the experiment area before and after the application of the genetic algorithm for one route. Connectivity shows the mutual transport accessibility of blocks in a given area. Each block has an average travel time (in minutes) to all other blocks. The longer the time, the worse the connectivity of one block with the others. The black outline of blocks in Fig. 6b shows the blocks where the connectivity values have changed: −1.92 min and −0.6 min, respectively.

4.2 Bus Routes Network Optimization

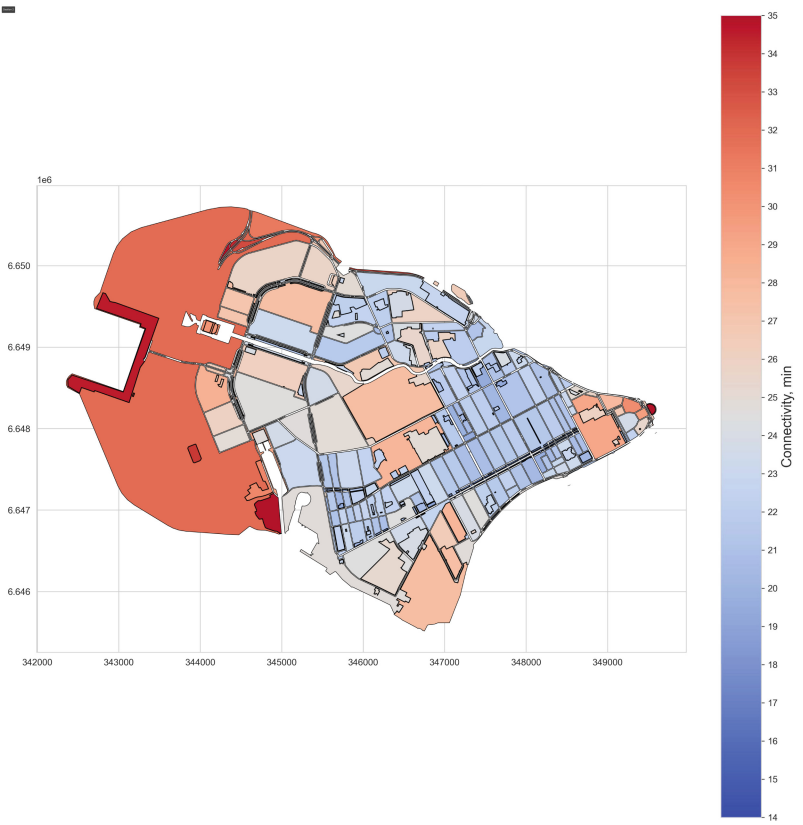
The existing routes are presented in Fig. 7a together with the current transport connectivity of the selected area (Fig. 7b). The average travel time for the entire given area is 23.3 min. Number of routes - 19. In this experiment, the number of bus stops does not change. However, there are stops in Fig. 7a that are not utilized by routes in the area. Such stops are part of routes that run in another territory but have one stop in the experiment territory. Such stops were subsequently used by the GA to modify the routes.

The transport connectivity metric shows how urban areas can be related to each other in terms of travel time when they are physically close or distant from each other. This approach allows us to integrally assess the quality of transportation service through time costs and to see which parts of the city are "cut off" from the rest through the public transportation network.

The result of the method - generated bus routes that optimized transport connectivity is shown in Fig. 8a. The number of routes has not changed. Improvement in terms of average travel time of about 1 min - 22.5 min (after optimiza-



(a) Existing bus routes

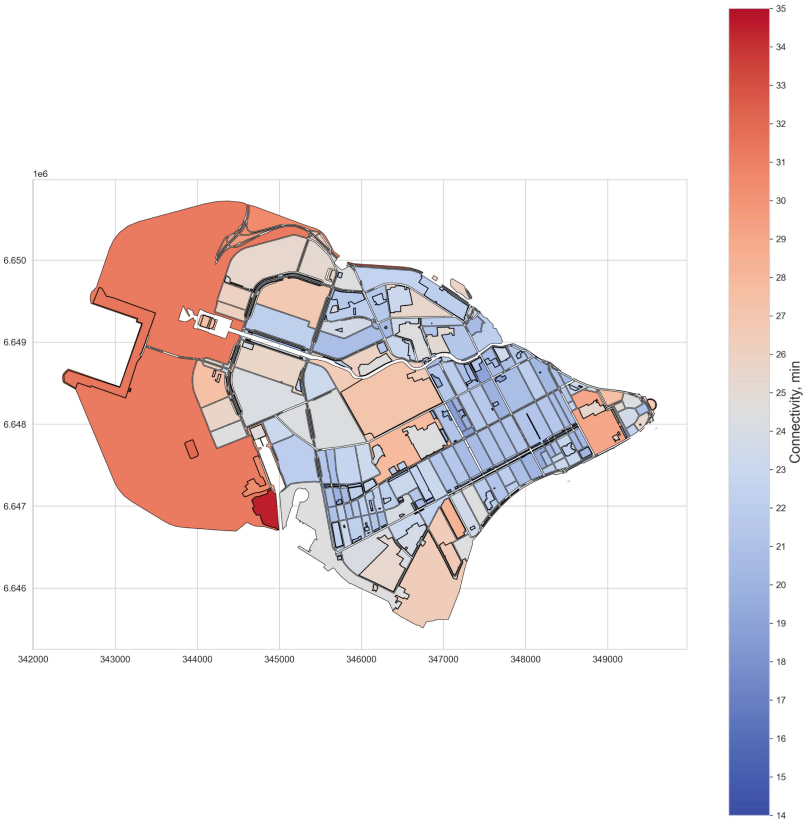


(b) Transport connectivity before optimization

Fig. 7. Existing bus routes and current transport connectivity in a given area



(a) New bus routes



(b) Transport connectivity after optimization

Fig. 8. New bus routes and optimized transport connectivity in a given area

tion). The increase is insignificant, but in the context of connectivity (Fig. 8b) it can be seen that some remote areas have become better connected to the rest.

5 Discussion

The proposed route generation method has the potential for development. The main disadvantages of the proposed approach are the lack of consideration of important data on transportation demand, speed of transportation at different times of the day, frequency of transfers, etc. At the same time, this is also an advantage compared to modeling, if such data are not available. Traffic delays due to congestion on the road network are not taken into account. If there are such delays and public transport does not run on segregated tracks, then in future works, it is necessary to take the loaded graph of the street-road network and take into account the actual speed of traffic. Future developments of the method may include the addition of transport demand data so that route generation is responsive to the need for transport services in urban areas.

6 Conclusion

The aim of this study was to develop a generative method for planning and optimizing public transport systems by generating new transport routes based on existing ones using open data. A genetic algorithm (GA) was selected as the generative method to obtain an optimal solution for the bus route network. The GA approach optimizes the bus route network by iteratively evolving a population of candidate solutions. Starting from an initial set of modified bus route configurations, the algorithm applies principles of natural selection - evaluation, selection, variation, and replacement - to gradually improve the solutions over multiple generations, ultimately converging on an optimal or near-optimal bus route design. This method is intended to determine the potential of the transport system and routes for development in non-optimized public transport systems or in areas that are just developing, where data on the future street and road network are available. Since transportation modeling is time-consuming and expensive, this method can provide an estimate based on available data.

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