SIMULATION MODEL FOR THE FORMATION OF DISTRIBUTIVE ROUTES IN A DYNAMIC URBAN ENVIRONMENT

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\textbf{Abstract.} The share of small shipments in the total volume of cargo transportation has increased significantly. However, irrational routes are formed, customers' requirements for timely delivery of goods are ignored, and vehicles of irrational carrying capacity are used on distribution routes, which significantly increases logistics costs and the cost of goods. The limitations and problems of existing solutions were analysed. Theoretic methods are not applicable to the Vehicle Routing Problem with more than 17 customers due to computational complexity. The heuristic methods that were examined focus on creating the shortest routes but do not consider customer priority, route restrictions, or potential service strategies. Therefore, a metaheuristic Genetic algorithm was chosen for route formation tasks. The research is aimed at developing a simulation model, which is based on the use of a genetic algorithm, to create optimal delivery routes for small shipments to customers within a city. The study includes modelling the route formation using a genetic algorithm for various types of cargo bicycles and trucks in a dynamic urban environment. As a result of simulation modelling, distribution routes were formed and operational parameters were optimized on cargo delivery routes in the city for various types of vehicles with different carrying capacities.

\textbf{Keywords:} Green Logistics, Dynamic Environment, Vehicle Routing Problem, Genetic Algorithm, Cargo Bicycles

1 Introduction

Logistics cost is a big part of the expenses for many manufacturers and companies in managing the movement and transportation of goods. Therefore, businesses wish to find ways to reduce logistics costs, especially at the “last mile” stage. One approach is to create optimal supply chains, which means finding the most efficient and cost-effective routes for transporting goods from the source to the destination. Achieving an optimal supply chain and

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route can lead to significant cost savings for businesses and enhance their competitiveness in
the market. On the other hand, companies strive to find ways to minimize the negative impact
on the environment caused by transportation activities [1]. By implementing environmentally
friendly practices and technologies, businesses can contribute to a greener and more sustainable supply chain [2]. In addition, one more challenge in the formation of optimal supply chains is a dynamic environment. Factors like varying demand, availability of goods, destination locations, and desired delivery times make it difficult to establish efficient supply chains. This study focuses on the formation of delivery routes for small shipments within a city, taking into account the dynamic nature of the cargo delivery problem.

However, for the transport of small loads in the city, the potential advantages of cargo bikes in terms of energy consumption, environmental impact, and road load are proposed as an alternative to trucks.

Thus, to optimize delivery routes for small consignments of cargo in a dynamic urban environment, it is necessary to develop models that take into account many conditions and restrictions.

2 Literature analysis

The most relevant in the logistics sector are the processes associated with the formation of optimal supply chains and optimizing the delivery of goods from the manufacturer to the customer.

Analysis of literary sources showed that organizations with lean supply chains should manage their supply chains to achieve efficiency, while organizations with agile supply chains should manage their supply chains with responsiveness toward customers’ needs in mind [3] and also based on the forecasting of demand volumes [4].

The problem of forming a route to visit a given set of locations and return to the starting point is known in the scientific literature as the traveling salesman problem (TSP). However, logistics systems are rather complex systems [3] that take into account the influence of a larger number of factors, such as the presence of a fleet of trucks with different capacities and different fuel efficiency, delivery at a given time, and time restrictions on the duration of transportation [5]. Effective management of the transportation process is significant [6], [7], [8] while ensuring the most rational use of the rolling stock and reducing transportation costs [9], and minimizing environmental pollution.

Analysis of literary sources showed that the problem of obtaining the optimal assignment of the goods available in the warehouses to the customers, known as Cost Minimizing Transportation Problem (CMTP), can be solved by the simplex method which is the effective theoretic algorithm [10].

In the case of transportation by one vehicle, the problem of the formation of a delivery route is reduced to the traveling salesman problem. In practice, the following algorithms are used to find a solution to the traveling salesman problem: the Bellman–Held–Karp algorithm, Prim's algorithm, and Kruskal's algorithm [11].

The Bellman–Held–Karp algorithm is a dynamic programming (DP) algorithm. The asymptotic of this algorithm is $O(n^2 \times 2^n)$, where $n$ is the number of vertices of the graph. This algorithm finds the optimal solution but is not applicable for $n>17$, due to too long execution time [12].

Prim's and Kruskal's algorithms are greedy algorithms. Prim's algorithm finds the minimum spanning tree for a weighted connected undirected graph. Kruskal's algorithm builds a minimum spanning forest for a weighted undirected graph. The found minimum spanning tree, i.e., a connected acyclic subgraph of the original graph containing all the vertices of the graph and having the least possible weight, allows us to solve the open
traveling salesmen problem. The asymptotic of these algorithms are $O(n^2 + m\log n)$, where $n$ is the number of vertices, $m$ is the number of edges in the graph [13].

In the case of an existing fleet of several vehicles, we get the Vehicle Routing Problem. This problem has many options, for example: having several garages, delivery within a specified time, different types of vehicles (different capacities or different fuel efficiency), etc.

The Bellman–Held–Karp, Prim's, and Kruskal's algorithms are difficult to generalize for solving the VRP. In addition, most often it is not clear how to do this.

Scientists suggest using the following methods for the solution of VRP for distributive, collected, and combined routes [14, 15]: the method of the shortest connecting network, Clark-Wright’s method [16], the method of the sums and its modification, the method of drawing up a route by adding columns, the method of ‘branches and boundaries’ [17], the method of fictitious knots and branches.

Most formation methods for distributive routes are based on the shortest routes [18]; however, they do not consider the priority of customers and the possible strategy of their service [19].

Theoretic methods demand considerable amounts of time for calculation and do not allow for forming optimum routes for a big number of the served customers. The risk of obtaining a non-optimal solution is very high when applying the classical approximate methods for the specified conditions and it does not guarantee effectiveness within an acceptable time period [20]. It should be noted that most often the VRP is carried out by simple and effective heuristics methods which allow for finding the necessary decision quickly. But at the same time, finding an optimal solution is not guaranteed [21, 22].

Today, methods that unite the flexibility of heuristics and severity of models by linear programming are developed. Such approaches allow receiving optimum or, at least, the best evidential decision [22]. Problems associated with route creation are often appearing and their solution is actively applying metaheuristic methods and algorithms. The most used of them are next: ‘local search’; ‘Evolutionary algorithms which are based on generating the individual populations’ [23], and ‘self-training’, namely artificial neural networks [24]. It is noted that the most efficient and promising metaheuristic approaches for the formation of cargo delivery routes in the dynamic environment are genetic algorithms (GA) [25, 26], and reinforcement learning method (LR) [27].

The basis of GA is based on the hypothesis that the optimal solution to a problem can be assembled from small structural elements. Individuals that contain some of the desirable structural elements are assigned a higher score. Repeated operations of selection and crossing lead to the emergence of ever-better individuals, passing these structural elements to the next generation, perhaps combined with other successful structural elements. This creates a genetic pressure that directs the population towards the emergence of an increasing number of individuals with structural elements that form the optimal solution. As a result, each generation is better than the previous one and contains more individuals close to the optimal solution.

GA is typically used to reduce the running time, time complexity, memory used, or space complexity. For many problems, a genetic algorithm is the simplest, the fastest, or both [28]. The genetic algorithm is simply generalized to the given options of the VRP. To do this, it is necessary to adapt the representation of the individual, its fitness function, and the operators of the genetic algorithm. The GA allows us to find fairly optimal delivery routes in the short time required for calculations [29] and can be adapted to changing problem conditions [30], such as the number of available vehicles, garages, the weight restrictions of the available vehicles park, etc.

RL is typically used to solve sequential decision-making problems. It applies mathematical processes to imitate natural learning. The goal of RL is to learn the best action
given the state of the environment, in order to maximize the overall rewards. In the context of logistics, the states of a system are usually characterized by the statuses of vehicles, customer demands and their locations, time windows, and inventory levels. Meanwhile, the actions can be vehicles’ routes, order quantities, or prices of delivery services. The rewards can be related to the profits generated, distance moved, energy consumed, or other performance indicators. The development and application of RL could play an important role in the future development of smart logistics [31].

In addition, the RL algorithm scales well as the VRP size increases [32], unlike heuristic algorithms and GA. Also, the RL algorithm trains once and then can solve similar-size problems with superior performance and competitive solution time [32], allowing it to be used in production and easily deployed.

Also, there are existing successful implementations of metaheuristic approaches for the formation of cargo delivery routes in the dynamic environment in real-world logistics companies. One of such examples is DoorDash, which provides a real-time platform for fulfilling consumer demand for merchant goods via a flexible Dasher fleet. Application of the RL model allowed achieving on average a 6-second improvement in delivery speed and a 1.5-second improvement in Dasher efficiency across all deliveries compared to previous heuristic algorithms [33].

Another example is a big logistics company Picnic. Each day tens of thousands of orders for Picnic’s customers are packed at warehouses. These orders are loaded into trucks and shipped to hubs, from which they are delivered to the customer’s doorstep. GA is successfully used to solve this truck scheduling problem [34].

However, there is a lack of comprehensive representation in the literature regarding research outcomes concerning the establishment of optimal routes in dynamic environments utilizing genetic algorithms. Delivery routes frequently encompass numerous variables, including customer locations, delivery times, cargo volume, and various constraints. Genetic algorithms excel at incorporating and optimizing such multidimensional spaces, proficiently managing tasks with numerous delivery points. Furthermore, genetic algorithms demonstrate scalability in accommodating diverse conditions, constraints, and process modifications. They can be tailored to different modes of transportation, route timetables, and delivery specifications, while also adeptly navigating shifting conditions such as traffic congestion, scheduling alterations, or additional delivery destinations, rendering them apt for dynamic route optimization. Concurrently, genetic algorithms are adept at optimizing multiple criteria, such as minimizing travel time, fuel consumption, or delivery expenses, thereby facilitating trade-offs among diverse objectives. Overall, genetic algorithms provide a powerful and flexible tool for solving complex delivery route optimization problems.

3 Purpose of the study

The object of the study is the process of cargo delivery in an urban dynamic environment. The subject of the study is the formation of routes in an urban dynamic environment based on the use of genetic algorithms. The purpose of the study is to develop a simulation model to optimize the process of transporting small consignments within the city in a dynamic environment.
4 Methodology

4.1 Formulation of the problem

Transportation of small batches of goods within city limits is carried out in a dynamic environment characterized by the random nature of demand parameters for cargo supplies, as well as the random quantity of customers, their locations, and the risk of having a sufficient amount of goods at distribution centres. During the operational planning of the goods delivery process within city limits, the problem arises of forming optimal routes when serving a large number of customers. In theory, this problem is referred to as the Vehicle Routing Problem (VRP), which cannot be solved for the described conditions using precise mathematical methods within an acceptable timeframe.

The research was carried out in the trading network of the LIDL company, which specializes in the trade of food products (more than 1,600 types of food products in a fixed assortment), as well as grocery and household goods. The supermarket group offers non-food products through the Lidl online store that can be ordered online.

The main office centre of the LIDL company is located in Karlsruhe, and the company has 39 large regional distribution centres in different states of Germany [35]. From these regional centres, products (food and household goods) are delivered by trucks to the supermarket network (urban distribution centres) in each state of Germany. Further, the products from the LIDL supermarket network are distributed to numerous small customers. The distribution of products is carried out either by courier delivery or by self-pickup.

Recently, especially during the COVID-19 pandemic, e-commerce has been rapidly developing. The trade network LIDL also demonstrates dynamic growth in online orders. Online customers include bakeries, pastry shops, cafes, restaurants, and the general population. Orders are placed daily. The order volume is a random variable and usually does not exceed 120 kilograms. Customer service for delivering their orders in the city is characterized by conditions of uncertainty, which are due to the random demand for products, changes in the number of customers, and therefore, the variability of delivery location points.

At the same time, the availability of the necessary quantity of products in LIDL supermarkets is characterized by risk conditions. The risk is determined by the probability of an insufficient quantity of products in certain supermarkets according to the orders they receive from consumers.

Thus, the distribution system of the city is characterized by a dynamic environment, shaped by the following factors:

− demand for products from small customers is a random variable;
− the daily number of customers is a random variable;
− the actual availability of goods in urban distribution centres is a random variable. Consequently, there may be a shortage of product inventory in the supermarket according to the received orders for that product;
− the need for vehicles and human resources varies depending on the aggregate volume of orders per day;
− the initial distribution of vehicles at loading points is random, depending on the organization of the product distribution process in the previous period.

Thus, there is a need for efficient route planning for the delivery of products when organizing the process of distributing small batches of orders from LIDL supermarkets to a set of customers within the city. Such distribution of products can be carried out using cargo bicycles or cars.

In the city of Karlsruhe, there are 6 LIDL supermarkets (Figure 1), as well as numerous bakeries, patisseries, and cafes. For the purposes of this study, 50 potential customers
(bakeries and restaurants) located in Karlsruhe were randomly selected. Their locations are shown in Figure 2.

It should be noted that all data regarding the volume of cargo in LIDL supermarkets, locations and names of potential LIDL customers, order volumes and product range are conditional and their values are accepted solely for the purposes of the simulation experiment.

Fig. 1. The locations of the 6 LIDL supermarkets in Karlsruhe city

Fig. 2. The locations of the selected 50 customers in Karlsruhe city

Two distance matrices were generated using the Google Maps Distance Matrix API between the 50 customers and 6 supermarkets for product delivery under the following
conditions by: car, cargo bicycles. An example of a distance matrix is given for cargo bikes. (Figure 3).

<table>
<thead>
<tr>
<th>To Location</th>
<th>Lidl 1</th>
<th>Lidl 2</th>
<th>Lidl 3</th>
<th>Lidl 4</th>
<th>Lidl 5</th>
<th>Lidl 6</th>
<th>Antalya</th>
<th>Arabischer Schawarma</th>
<th>Asmara Restaurant</th>
<th>Back Eck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lidl 1</td>
<td>0.00</td>
<td>3.85</td>
<td>2.69</td>
<td>1.63</td>
<td>3.59</td>
<td>4.31</td>
<td>1.58</td>
<td>1.58</td>
<td>0.81</td>
<td>0.48</td>
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<td>6.27</td>
<td>3.36</td>
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<td>5.58</td>
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<td>Lidl 4</td>
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<td>3.45</td>
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<td>4.11</td>
<td>2.65</td>
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<tr>
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<td>6.41</td>
<td>1.13</td>
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<td>1.27</td>
<td>2.53</td>
<td>2.08</td>
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<td>Arabischer Schawarma</td>
<td>1.73</td>
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<td>2.97</td>
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<td>Back Eck</td>
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<td>3.59</td>
<td>2.87</td>
<td>1.97</td>
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<td>2.08</td>
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<td>0.96</td>
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<tr>
<td>Badische Backstub (Karlsruhe)</td>
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<td>1.94</td>
<td>2.25</td>
<td>4.20</td>
<td>3.16</td>
<td>0.69</td>
<td>0.88</td>
<td>2.00</td>
<td>1.31</td>
</tr>
</tbody>
</table>

Fig. 3. Fragment of the distance matrix between customers and supermarkets for product delivery by cargo bicycles

To conduct the research, different types of vehicles were selected including different fuel-consumption trucks (diesel-powered, electric) and cargo bicycles with different payload capacities.

4.2 Mathematical formalization of the problem

The total distance (1) of the selected type of vehicle has been selected as the criterion for route optimization.

\[ \sum_{i=1}^{n} d_i \rightarrow min \]  

(1)

where \( n \) – the number of vehicles;
\( d_i \) - the length of the route of the \( i \)-th vehicle.

The operating time of the \( i \)-th vehicle on the route is denoted as \( T_{route}^i \) and can be calculated using formula (2).

\[ t_{route}^i = \sum_{j=1}^{m_i} t_{ij} + \frac{d_i}{V_{tech}} \]  

(2)
where $V_{tech}^i$ – average technical speed of the $i$-th vehicle, which shows how many kilometers the vehicle covers on average per hour of travel;  
$m_i$ - the number of transfers in the route of the $i$-th vehicle;  
$t_{ij}$ – the loading-unloading time of cargo for the $j$-th transfer, which is calculated by formula (3).

The loading-unloading time is determined by the next formula, in hours:

$$ t = \begin{cases} 
\frac{15 + 3 \times \max(0, q \times \gamma_{stat} - 0.1)}{60}, & q \leq 0.35 \\
\frac{2 \times (3 \times \lceil q \rceil \times \gamma_{stat} - 1) + 13}{60}, & q > 0.35 
\end{cases} $$  

(3)

where $q$ – the volume of cargo being loaded and unloaded, is measured in tons;  
$\gamma_{stat}$ – load capacity utilization coefficient, taken in this study, is 0.8 for the transportation of food and household goods.

The model incorporates the following constraints:

- the required number of vehicles for efficiently distributing products from supermarkets to customers must not be less than the actual number of vehicles;  
- the working time on routes does not exceed the duration of the supermarket's working day ($T_{max}$);  
- the total driving distance on the routes does not exceed the maximum driving distance of the selected vehicle assigned for the delivery.

$$ \forall i \in [1,n]: t_{route}^i \leq T_{max} $$  

(4)

As a result of route planning, it is necessary to assess the performance indicators of the vehicles:

- total driving distance per day;  
- total empty driving distance;  
- total loaded driving distance;  
- required number of vehicles;  
- time spent on routes.

Assumptions of the model:

- it was assumed that the supermarket operates for a duration of $T_{max} = 12$ hours;  
- demand for products from small customers is a random variable measured in kilograms that follows a normal distribution with parameters mean $\mu = 60$ and standard deviation $\delta = 20$;  
- the product range does not require specific temperature conditions during transportation;  
- all supermarkets in the network have an identical product range available for orders;  
- all transport vehicles used for goods delivery are assigned to supermarkets and start and finish their workday at the designated locations allocated to them;  
- cargo bicycles have an average technical speed of $V_{tech} = 10$ km/h, while cargo trucks have an average technical speed of $V_{tech} = 22$ km/h.
5 Simulation model for optimizing cargo transportation routes in a dynamic urban environment

For modelling purposes, a random demand was generated following a normal distribution for the 50 selected potential customers in Karlsruhe city. Similarly, the number of products in supermarkets was randomly generated, also following a normal distribution. The generated quantities allowed for a maximum deviation of 10% from the required amount to fulfill the generated demand. Thus, due to product shortages in supermarkets' warehouses, some customers require goods to be delivered from supermarkets that are not the closest to them.

To achieve the optimal allocation of goods from supply to demand, where each customer is assigned to the most suitable supermarket, an open cost-minimizing transportation problem was solved. In Figure 4, a part of the optimal transportation plans is presented for delivery by bicycles. These plans take into account the generated supply and demand and help determine the best way to distribute products from the supermarkets to individual customers.

<table>
<thead>
<tr>
<th></th>
<th>Lidl 1</th>
<th>Lidl 2</th>
<th>Lidl 3</th>
<th>Lidl 4</th>
<th>Lidl 5</th>
<th>Lidl 6</th>
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<tr>
<td>Just Fresh - Arabisches Restaurant</td>
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<td>0</td>
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<td>0</td>
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<tr>
<td>KOLO City Pizza &amp; Kebaphaus</td>
<td>87</td>
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<td>Kabibi Karlsruhe Schawarma und Falafel</td>
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<tr>
<td>Memo Restaurant</td>
<td>54</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tbody>
</table>

Fig. 4. A part of the optimal transportation plan, which allocates the goods from supply sources to demand destinations when using bicycle delivery
A genetic algorithm was implemented to determine the specific order of transfers and assign the appropriate vehicles for each transportation. We defined a genetic individual as a list containing numbers ranging from 0 to (N-1)+(M-1), where M denotes the number of vehicles. The first N numbers represent the indexes of the required deliveries from the supermarket to the customer, derived from the optimal transport plan. The remaining M-1 numbers serve as delimiters, dividing the list into separate routes for each vehicle. When a route between delimiters is not empty, the respective vehicle is responsible for delivering the cargo in the order specified within the individual between those delimiters. Furthermore, we considered the scenario where a vehicle can carry cargo for multiple customers in a single trip. If an individual includes consecutive deliveries from a single warehouse, we incorporate them into a single distribution route, taking into account the maximum capacity of the vehicle.

The fitness function, expressed as formula 6, takes into account several factors. These factors include the total length of all routes, penalties for violating the time duration limit of a route, and penalties for violating the path length limit. Additionally, it should be noted that penalties are applied not only for exceeding the time limit of a route but also for falling below it. This is done to optimize the required number of vehicles for delivering goods, as it is not efficient to have multiple short routes completed by different vehicles in a short period of time. However, the penalty for exceeding the time limit is ten times larger than the penalty for finishing early. α is predetermined as model hyperparameters serve as the scaling factor for deviating from the maximum route time.

The important point to note is that when we increase the penalty for deviating from the maximum route time in the fitness function (α from the Formula 5), we can further optimize the number of vehicles used for delivering cargo.

The genetic algorithm consists of several hyperparameters. A popular approach to finding optimal combinations of these hyperparameters is through a grid search method. We randomly generated an initial population of 1000 individuals. The number of generations was chosen to be 250. During the search for optimal hyperparameters, various parameters were explored, such as genetic selection operator (tournament selection of size 2, tournament selection of size 3, roulette wheel selection), crossover operator (partially matched crossover, uniform partially matched crossover, or order crossover), mutation operator (swap mutation, inversion mutation, or scramble mutation), crossover probability (0.7 or 0.9), mutation probability (0.2 or 0.4), hall of fame size (15, or 25), and α from the fitness function (1, 2, 3, 4). Figure 5 shows a histogram that represents the total lengths of routes for the best individual in each generation during the process of finding the best set of hyperparameters for a genetic algorithm through a method called grid search. It can be mentioned that only a part of hyperparameter sets produce good results. The best hyperparameter settings that yielded the lowest total distance of the route were determined as follows: the selection operator is tournament selection of size 2, the crossover operator is a partially matched crossover, the mutation operator is swap mutation, crossover probability is 0.7, mutation probability is 0.4, hall of fame size is 25, and α=3.
Fig. 5. The histogram displays the total lengths of routes for the best individual in every generation throughout the search for the optimal set of hyperparameters.

As a result, the use of genetic algorithms allows us to find a solution that is close to the best possible one, taking into account all the constraints, within a reasonable time frame during operational planning.

6 The discussion of the results

The distributive route for small consumers involves loading goods into a warehouse for several consumers at the same time and then delivering these goods to consumers sequentially. If the same vehicle needs to make multiple deliveries in a row from the same supermarket, and the vehicle can carry all the goods needed, then all cargo will be loaded onto the vehicle and delivered one by one to each customer. Creating such routes will allow us to utilize the full capacity of vehicles.

Fig. 6. The lowest and average values of the fitness function for the populations during the execution of the genetic algorithm.
Figure 6 displays the graphs of the minimum and average values of the fitness function in the population, depending on the generation. We can observe that increasing the number of generations does not significantly improve the solution. Therefore, we can conclude that we have reached the optimal solution that the genetic algorithm can provide within the given constraints.

Figure 7 presents the performance metrics for the route generated through the application of a genetic algorithm with $\alpha = 0.8$ for VUF XXL bicycle-based deliveries. In this particular case, we only need 3 bicycles, and the total distance of the routes is 86.82 km.

Route for the bicycle (VUF XXL 4): Lidl 4 $(32 \text{ kg})$ → Bäckerei Meier 5 $(82 \text{ kg})$ → Firo Kebap $(0 \text{ kg})$ → Lidl 1 $(40 \text{ kg})$ → Restaurant Mogogo $(99 \text{ kg})$ → Truvas Restaurant $(0 \text{ kg})$ → Lidl 1 $(14 \text{ kg})$ → Just Fresh – Arabisches Restaurant $(48 \text{ kg})$ → Da Nang $(36 \text{ kg})$ → Oxford Pub – Bier & Burger $(49 \text{ kg})$ → Arabischer Schawarma $(0 \text{ kg})$ → Lidl 3 $(74 \text{ kg})$ → Antalya Restaurant $(43 \text{ kg})$ → Bäckerei Konditorei Steinbeck $(0 \text{ kg})$ → Lidl 6 $(76 \text{ kg})$ → Restaurant Hasen Karlsruhe $(69 \text{ kg})$ → Chiang Mai Thai Restaurant $(68 \text{ kg})$ → Chinese Fast Restaurant $(0 \text{ kg})$ → Lidl 4 $(0 \text{ kg})$

Number of loaded routes: 14
Loaded driving distance: 14.8 km
Empty driving distance: 8.67 km
Deadhead driving distance: 3.57 km
Driving time: 2.46 hours
Loading and unloading time: 3.5 hours
Total driving distance: 27.04 km
Total time: 5.96 hours

Total energy consumption: 1.3 kWh
Total CO2 emissions: 694.56 grams
Total time: 20.4 hours
Total loaded driving distance: 47.78 km
Total empty driving distance: 28.64 km
Total deadhead driving distance: 10.4 km
Total driving distance: 86.82 km

Fig. 7. The performance indicators for deliveries processed by the VUF XXL cargo bicycle using distributive routes when applying a genetic algorithm

Similarly, performance metrics for routes created using a genetic algorithm for deliveries by other alternative vehicles were obtained (Table 1).

Thus, as a result of simulation modelling of the process of delivering small consignments of goods in an urban dynamic environment, distribution routes were formed and operational parameters on the routes were optimized using various vehicles (total mileage; total mileage when empty; total mileage with cargo; required number of vehicles/bicycles; time spent on routes; total energy expenditure; total greenhouse gas emissions).

Additionally, all time and distance constraints are met, and the travel times for all vehicles are balanced with each other.
Table 1. The performance indicators for formatted distributive routes for various types of vehicles

<table>
<thead>
<tr>
<th>Indicator</th>
<th>DHL Cubicycle</th>
<th>VUF XXL</th>
<th>FULPRA ROLL 3000L</th>
<th>Volkswagen Golf VIII</th>
<th>Ford E-Transit</th>
<th>Sprinter Cargo Van 3500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Required number of vehicles per day, units</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Total distance traveled, km</td>
<td>96.12</td>
<td>86.82</td>
<td>65.98</td>
<td>76.18</td>
<td>73.75</td>
<td>69.16</td>
</tr>
<tr>
<td>Total distance traveled with cargo, km</td>
<td>50.1</td>
<td>47.78</td>
<td>41.34</td>
<td>50.29</td>
<td>49.3</td>
<td>47.79</td>
</tr>
<tr>
<td>Total distance traveled without cargo, km</td>
<td>46.02</td>
<td>39.04</td>
<td>24.64</td>
<td>25.89</td>
<td>24.45</td>
<td>21.37</td>
</tr>
<tr>
<td>Total delivery time, h</td>
<td>22.11</td>
<td>20.4</td>
<td>19.1</td>
<td>20.37</td>
<td>20.13</td>
<td>19.67</td>
</tr>
<tr>
<td>Total energy consumption</td>
<td>1.34 kWh</td>
<td>1.3 kWh</td>
<td>2.9 kWh</td>
<td>4.57 L</td>
<td>25.08 kWh</td>
<td>6.22 L</td>
</tr>
<tr>
<td>Total daily CO2 emissions, g</td>
<td>768.96</td>
<td>694.56</td>
<td>527.84</td>
<td>8760.7</td>
<td>10214.3g</td>
<td>10906.53</td>
</tr>
<tr>
<td>Required number of drivers per day, units</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>
For the convenience of applying the simulation model, software with a user-friendly interface has been developed, allowing input of data about suppliers, customers, and information about the actual availability of cargo from suppliers, as well as the current demand for freight from customers. (Fig. 8, 9).

**7 Conclusions**

It has been determined that the operational planning of delivery routes for small consignments of goods should be carried out in a dynamic environment, which is characterized by the stochastic nature of the demand for transportation, the changing number of customers, and their location within the service region and taking into account the risk conditions of insufficient quantities of cargo at a certain point of departure.

The methods applicable to the Vehicle Routing Problem were analysed, and their advantages and disadvantages were identified. As a result of the analysis, a Genetic algorithm was selected for the formation of cargo delivery routes.

A simulation model of route formation in a dynamic urban environment has been developed based on the use of a genetic algorithm, the parameters of which are selected for the given operating conditions of the city's distribution system. As a result of simulation modelling, distribution routes were formed and operational parameters were optimized on cargo delivery routes in the city when using cargo bicycles and cars of various carrying capacities: total mileage per day; total mileage when empty; total mileage with cargo; required number of cars/bicycles; time spent on routes; total energy costs; total greenhouse gas emissions. The suggested approach for operational planning considers various vehicle limitations and ensures a balanced distribution of the workload to maximize efficiency in the delivery process.

The proposed model can be used by transport, logistics, manufacturing, and trading companies in the operational planning of distribution routes for small consignments of cargo within the city, and can also be used for educational purposes and research.
Further research will be aimed at comparing modelling results when forming cargo delivery routes in the case of using the Genetic Algorithm and Reinforcement Learning in order to identify the best algorithm for finding the optimal solution. Simulation experiments will be carried out for various scenarios of the delivery process and various characteristics of cargo demand for further analysis of the obtained statistical data.

References


