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ENERGY EFFICIENCY OPTIMIZATION OF LAST MILE SUPPLY SYSTEM WITH REVERSE LOGISTICS CONSIDERATION

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Abstract: Last mile supply system takes great importance in the designed supply chain management, especially in the big urban areas, where various goods delivery locations should be tackled. Transportation routes and vehicles play a critical share in the optimization of the energy spent in this system because it is considered a complicated case due to its high solutions possibilities. Also, part of these transport processes is considered reverse logistics, where the goods take the way back, starting from the customer. Using a metaheuristic optimization is usually a good way to increase operations efficiency and save time and energy, next to raising sustainability. Within this paper, the last mile supply system within urban areas focusing on the goods' delivery and collection tasks is presented. The model design is described, mathematical optimization modelling is detailed, and a case study to investigate the impact of using diesel and electric trucks on energy efficiency is solved. After an introduction and theoretical background that includes a brief literature review, the designed system and used methodology are described. The designed system incorporates cloud computing, real routes of vehicles, analysis of collected data, energy consumption optimization, and time windows. Also, a mathematical model is developed with the aim of optimizing the total energy consumption. Real thirty locations in Budapest in the VII district are described and used as a case study for finding the solutions of the optimized taken routes and energy consumption by the genetic algorithm for both diesel and electric trucks. In the end, the results are analyzed and compared against a random solution to clarify the presented optimization's effectiveness.

1 Introduction and theoretical background

The city logistics area is a rich topic to tackle and research regarding its diverse implementations, especially during recent years because of the numerous various innovations in both transportation and Industry 4.0 areas. The renewable energy evolutions in transport vehicles like e-cars create a wide scope to adopt them in the city logistics applications considering the relatively shorter distances in the city logistics area compared to the outside cities. Moreover, Industry 4.0 applications, which depend on the Internet of Things (IoT) and artificial intelligence, support innovating smart solutions to shorten the required time and road distance while collecting and analyzing information at the same time, giving the capacity to examine them. On the other hand, sustainability is a critical topic that is represented in the Sustainable Development Goals (SDGs), such as the 11th goal, "sustainable cities and communities" [1], which gives it a priority to be tackled in research. The investigation of reducing the spent power, emissions, and contamination aspects was advised to be researched for its positive influence on the climate and environment. Studying these new solutions has significantly raised in many aspects for showing the importance of applying them in reality [2]. Last mile logistics is the latest stage of the supply chain, and it involves a particular share of the overall delivery cost and energy. Industry 4.0 applications allowed the possibility of reducing the time of the order execution within the real-time handling of open tasks in the package delivery service providers' network. Therefore, the last mile logistics optimization shows significant potential for researchers, and it creates a challenge for them [3]. Depending on the energy efficiency's significance of last mile services that are represented by package delivery service providers, it is expressed that this research area is so valuable. The rising value of resources, cost, and power in supply chain applications and the purpose of detecting design and operation strategies enforced in real-time are strong motivations for researching this area [4]. Real-time intelligent scheduling in the last mile delivery was also presented [5] as a developed methodological approach based on the Industry 4.0 applications. Depending on a systemic literature review [4] that was based on 231 articles, more attention and research were required in the last mile supply area, especially with considering the metaheuristic algorithms for energy efficiency aspect. The genetic algorithm (GA) was presented as an effective metaheuristic algorithm in many fields [6], such as operation management, scheduling, and inventory control.

An important aspect of the last mile transportation is reverse logistics (RL) that is one of its definitions is [7] “the process of planning, application, control of the operation, cost and flow of raw materials, the inventory process, finished products, the information related, from the point of consumption to the point of origin, to recover or create value or proper disposal”. RL has distinct characteristics, for example, critical uncertainties of time, quality, and quantity supplying next to the operations' complexities. A framework founded on the reverse stream of distribution starting from the producer until the user and backward to the producer was proposed [8]. It defined the motivation types mainly as the economic amount, governance legislation, and ecological image, while disposal kinds were defined as reuse, repair, recycling, and re-manufacturing. Another framework for RL defined five directions: (1) return causes; (2) reception body; (3) product types and their characteristics; (4) recovery operations and settings, and (5) involved actors and their roles [9]. In order to clarify the RL problems and develop solutions, modelling techniques were used [10], but the prime problem is the need for a high number of variables considered. In a study [11], five strategic operators were considered significant for the RL that are environmental concerns, quality, costs, customer service, and political/legal considerations. Also, RL was researched [12] within the composed framework of environmental operators (regulation and environment respect) and business operators (customer satisfaction and returns) [13]. However, a need for further research on the aspects of strategic and organizational frameworks of RL was confirmed [14], which includes integrating the RL in the designed supply system, for instance. Considering RL for sustainable aspect was confirmed [9] as one of the main factors in the city logistics area, particularly from an Industry 4.0 technologies point of view.

The following points sum up the presented theoretical background in the chapter:

- Last mile transportation operations are a rich area to research considering its various application and tools to be adopted especially considering the innovative Industry 4.0 technologies and applications.
- While RL takes a primary share of the transportation applications in city logistics, it still requires more research to investigate its results and effects.
- Using metaheuristic optimization is considered an effective method to optimize the last mile transportation processes. The GA showed strong optimization results in many areas including the logistics area. Also using the direct lines (not real) distances between the location is a common way to be used in previous research.
- Electric vehicles showed promising leverage for raising energy efficiency. However, further research on this adoption and its effects is required to find out deeper outcomes.

2 System description and methodology

The last mile transportation system expresses the operations that take place under the city logistics aspect. While the goods storage station represents the last echelon of where the goods are to be delivered to the specified locations, RL also happens to be collected from specified locations to be moved to the goods storage station. This system is represented as a scheme in Figure 1. Routes and consumed time are calculated depending on Open Route Service, which gives real distances and time. This service was developed by HeiGIT gGmbH [15].

The locations express both types of goods' delivery and collection. It shows how RL operations were integrated into the supply system. Cyber management expresses the cloud system where the data are stored, analyzed, and calculated. Therefore, information flow is considered between the cyber management and IoT tools within the system parts, such as the trucks and goods storage station GA is used in this system to calculate the optimized energy efficiency solutions for doing the goods' delivery/collection. However, in this study, an upgrade step is used regarding the iteration number. Instead of raising the iteration number to reach better results, three runs are done, and the best value will be selected as the optimized result. The optimization is represented in Figure 2 next to the used locations’ order coding for two trucks case that is applied in the case study of this article. After the separation of the two trucks' location orders, the locations will be reordered separately, considering that location 0 is the start and end location for both trucks. Therefore, the last location is transferred into 0 after separating the two locations' orders. This process is illustrated in Figure 2, which is more detailed in mathematical modelling.

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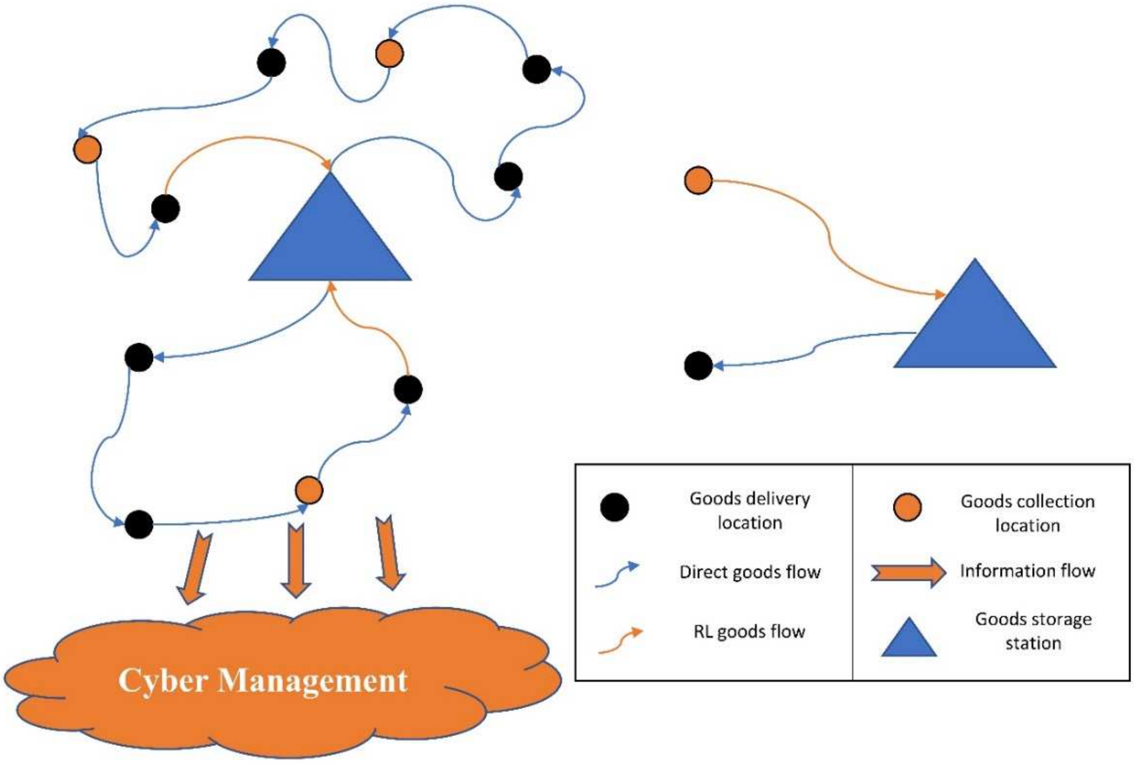

Figure 1 Last mile supply system scheme

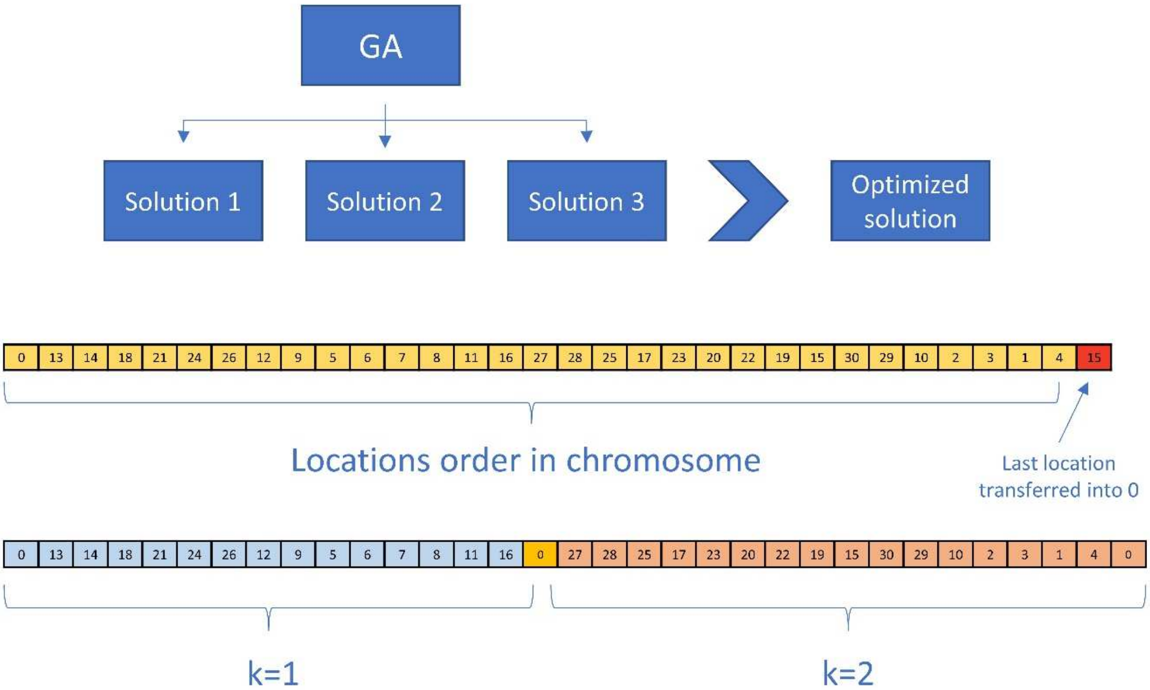

Figure 2 GA optimization methodology

This chapter presented the designed system and methodology. Chapter three details the mathematical modeling of this system to optimize energy efficiency. Chapter four presents a validation for the mathematical modeling for 30 locations in VII District in Budapest by using diesel and electric trucks. A random solution is to be used to compare the optimization efficiency. Chapter five discusses the results and expresses the possible further research directions. Finally, a summary that sums up this study. This scientific contribution that defines the aim of this paper is summarized in the following points:

1. Designing last mile goods transportation system with integrated RL operations. This system considers incorporated Industry 4.0 technologies such as IoT and cloud data analysis.
2. Presenting an elaborated description for the mathematical model depending on the efficiency of the spent energy and designed system. It is important to mention that part of the mathematical model is adopted from previous research [16] while the parts are developed within this study.
3. Employing the actual routes method between locations in city logistics applications instead of the conventional direct lines to achieve realistic results. Also, a case study of 30 locations in VII District in Budapest is discussed and analyzed.
4. Finding the optimized energy consumption by using the actual real routes by GA algorithm for both diesel and electric trucks with a clear comparison and discussion with a considering for a random solution. Moreover, GA optimized solution was updated with an explanation of the used coding system.

3 Mathematical modelling

In the vehicle routing problem (VRP), it is worked on finding the shortest travel distance roads with starting in and returning to the same place for serving a group of customers [17]. The VRP has been applied in various applications, including but not bounded to city logistics goods' delivery and collection.

However, there is a second way where a few researchers considered the goods' delivery/collection problem to be an arc routing problem (ARP) instead of the VRP which is called a node routing problem. The prime variance between ARP and VRP is that the concentration goes on the routes instead of nodes in the ARP because the vehicles carry out their provided services whilst traversing the routes. Therefore, the goods' delivery problem considers the clients are located over the roads, from an arc point of view not at the nodes. Overall, because there is a specific set of locations that should be serviced in this study; hence, the VRP model was selected. Furthermore, in particular situations, the tackled locations' density over a specific street is very big that the better approach for solving the routing problem is the ARP instead of the VRP [18]. Such situations do not appear in this study, as the locations are somehow scattered around the city center. Also, the CVRP is considered as an adoption of the VRP while applying capacity constraints. The CVRP in our mentioned system is identified as goods delivery and collection from and to a group of locations using homogeneous trucks that have a specified capacity, which is not possible to be violated; each one of these trucks starts from and returns to a specific same location [19]. The used model of this study is detailed in this chapter, where n is the visited locations' number and m is the used trucks' number by homogeneous trucks that are defined as $K = \{1, 2, \dots, m\}$, the mentioned trucks are stationed at the goods storage station at the beginning. The index set $I = \{0,1,2, \dots, n\}$ refers to the locations where $i, j \in I$. $i = 0$ refers to the goods storage station location. For each location, there is q_i goods' quantity that should be delivered/collected. The positive value refers to the delivery task, while the negative value refers to the collection task. D_{ij} refers to the real road distance from location i to location j, where $i \neq j$, and it should have a non-negative value.

The model of this study considers the capacity of both the trucks and the goods, where:

- C refers to the maximum goods' amount that is possible for the trucks to transport.
- q_{max} refers to the maximum goods' amount in each location that is possible to be tackled.

  Additionally, the model presents a time limit as well, where:
- T_{max} refers to the maximum specified time for the whole process.
- t_k refers to the time that is taken by truck k to finish its route and go back to the start location.

The total energy consumption (TE) is the defined objective function where it aims to be minimized. It refers to the spent kWh by the used trucks during the goods delivery/collection system, which is found depending on the distance length, and specific fuel consumption rate [2]. The following mathematical modeling is based on previous research [16] that tackled a waste management system. Within this study, the previous model was adopted and developed to tackle the described system in chapter two. This modeling has two decision variables. X_{ijk} that is 1 if vehicle k proceeds from location i to location j; otherwise, it is 0. Y_{ik} that is 1 if location i is part of the vehicle k route; otherwise, it is 0.

The objective function is described as:

$$\text{TE} = \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=1}^{n} X_{ijk} . Dij . c_{ijk}^{T} \rightarrow min \quad (1)$$

where D_{ij} is the real distance from location i to location j, X_{ijk} is the decision variable, k is the number of trucks, and c_{ijk}^{T} refers to the specific fuel consumption that is defined as

$$c_{i,j,k}^{T} = c_{kmin}^{T} + ((c_{kmax}^{T} - c_{kmin}^{T}) / c_{kmax}^{T}) q_{ijk} / ((q_{ijk} / c_{kmax}^{T}) + C - q_{ijk}) \quad (2)$$

where c_{kmin}^{T} and c_{kmax}^{T} refer to the lower and upper bounds within the specific fuel consumption depending on the weight of the goods, and q_{ijk} represents the weight of the goods picked up by truck k when moving from location i to location j.

Subject to the following constraints:

$$\sum_{i=0}^{n}\sum_{k=1}^{m} X_{ijk} = 1 \ \forall j \in I \quad (3)$$

$$\sum_{j=1}^{n} X_{ijk} = \sum_{j=1}^{n} X_{jik} = Y_{ik} \ \forall i \in I;\ k \in K \quad (4)$$

$$\sum_{i=0}^{n}\sum_{k=1}^{m} q_{jik} - \sum_{i=0}^{n}\sum_{k=1}^{m} q_{ijk} = c_j \ \forall j \in I \quad (5)$$

$$\sum_{i=1}^{n} c_i X_{ijk} \le C \ \forall j \in I;\ k \in K \quad (6)$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} X_{i0k} = 1 \quad (7)$$

$$\sum_{i=1}^{n} q_i \le \sum_{k=1}^{m} C_k \quad (8)$$

$$max(t_1, t_2, \dots t_m) < T_{max} \quad (9)$$

Equation (3) ensures that only one vehicle visits every location. Equation (4) states the condition of continuity. Equation (5) states that the truck does deliver/collect the goods at the visited location. Equation (6) states that the carried goods within the tour should not overrun the capacity of the vehicle. After the last location is visited, the truck returns to the goods storage station according to equation (7). Equation (8) ensures that the total goods' weight for the allocated locations is less than the overall capacity of used trucks. Equation (9) states that the taken time by each truck does not exceed the allocated time for the process. Used notations are illustrated in Table 1.

Table 1 Used notations

Notation	Description
n	Visited locations overall number.
m	Trucks overall number.
K	The indices group represents trucks.
I	The indices group represents visited locations.
$i, j \in I$	Two arbitrary indices denote a visited location.
$k \in K$	An arbitrary index of a truck.
q_i	A value representing the goods weight of location i.
q_{ijk}	A non-negative amount represents the goods' weight in truck k while moving from location i to location j.
C	The truck's maximum capacity of goods.
T_{max}	The specified maximum time to finish the entire process.
t_k	The time that is taken by truck k to finish its route and go back to the start location.
q_{max}	The maximum goods' capacity in each location is to be tackled.
X_{ijk}	A decision variable that is 1 if vehicle k proceeds from location i to location j otherwise, it is 0.
Y_{ik}	A decision variable that is 1 if location i is part of vehicle k route, otherwise, it is 0.
TE	Total optimized energy consumption.
c_{ijk}^{T}	The specific fuel consumption for truck k when moving from location i.
c_{kmin}^{T}	Specific fuel consumption's lower bound.
c_{kmax}^{T}	Specific fuel consumption's upper bound.

4 A case study in Budapest

For validating the presented mathematical model, a case study that consists of thirty locations in the VII District in Budapest is described and analyzed. The actual real routes are used to find the total optimized energy consumption of the used trucks in kWh by using the GA metaheuristic algorithm. The solutions are to be compared against a random solution for each case to outline the optimization efficiency. Within this case, the lower and upper bounds of specific fuel consumption are considered the same as in a previous study [2] while assuming an average speed of 25 km/h in the city center. The time window is an essential consideration since there is interaction with customers, moreover, electric trucks have limited operational time usually depending on their battery capacity. Used truck specifications are presented in Table 2.

Table 2 Used truck specifications

	c_{kmin}^{T}	c_{kmax}^{T}	q_{max}	C	T_{max}
Diesel	20 kWh/km	41 kWh/km	100 kg	600 kg	3 hours
Electrical	11 kWh/km	18 kWh/km	100 kg	500 kg	2 hours

For obtaining the locations' data, a generating method was used [16]. Two geographical locations were chosen as geographical boundaries to find the locations' data in the VII District in Budapest. The Haversine formula was used to calculate the diameter depending on the distance between those two selected locations. Additionally, a circle was shaped depending on the calculation of the centric location over the segment amidst the two boundaries. Then, the locations were generated in the circle boundary in a random way using a uniform distribution. After that, the generated locations were ensured that they represent convenient locations on the map, and a few of them were manually adjusted. The goods' weight in every location was generated following a uniform distribution in a random way as well. Table 3 shows the goods' weight and their locations.

Table 3 The goods' weight and their locations

ID	Latitude	Longitude	Goods' weight (kg)
0	47.501374	19.093158	-
1	47.497593	19.055899	33
2	47.498133	19.057511	-9
3	47.497602	19.058477	74
4	47.496396	19.059368	88
5	47.497686	19.060825	-68
6	47.498425	19.061217	67
7	47.500001	19.059982	71
8	47.499277	19.064749	-17
9	47.497431	19.067606	1
10	47.49691	19.068347	20
11	47.498606	19.069738	52
12	47.498354	19.073727	-40
13	47.499479	19.074273	29
14	47.500382	19.073401	-18
15	47.504214	19.074972	19
16	47.502627	19.080453	8
17	47.502982	19.081409	-40
18	47.505488	19.082116	61
19	47.507706	19.081259	37
20	47.509121	19.081838	-17
21	47.508908	19.083005	81
22	47.508367	19.083632	52
23	47.50606	19.084608	76
24	47.504937	19.085591	-14
25	47.503217	19.08456	43
26	47.50247	19.08532	50
27	47.504233	19.087563	-39
28	47.503577	19.088435	39
29	47.501554	19.065602	-40
30	47.50562	19.069682	40

For implementing the GA, the following parameters were considered: population size is 100, the crossover probability is 40%, mutation probability is 20%, the number of iterations is 100, and the selection method is tournament selection. The utilized machine has an i7-7500U 2.70 GHz processor, and 8 GB of RAM.

4.1 The first case of diesel trucks

In this case, two trucks were needed. Total consumed energy, total distance, needed time for the process, and initial weights for each truck, in this case, are summarized in Table 4. Execution of the whole code is 14.62 s. Also, the total energy and distance for a random solution are mentioned.

Figures 3 and 4 show the actual routes for the optimized solution and random solution of this case. Red and blue colors are used to distinguish each truck's route.

Table 4 Results of diesel trucks case

	Total energy (kWh)	Total distance (km)	Time (min)	Initial weight (Truck 1)	Initial weight (Truck 2)
Solution 1	606.17698	29.24704	50.06	105	197
Solution 2	**534.2343**	**25.94166**	**39.331**	**152**	**150**
Solution 3	548.88179	26.33791	43.3312	157	145
Optimized solution	**534.2343**	**25.94166**	**39.331**	**152**	**150**
Random solution	1429.40629	66.1656	-	-	-

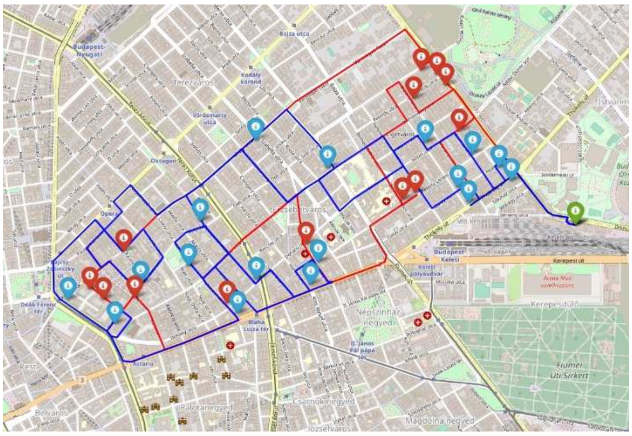
Figure 3 Optimized solution for the first case (diesel)

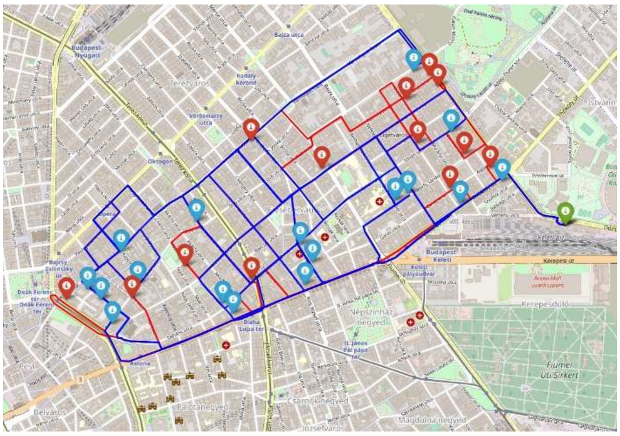
Figure 4 Random solution for the first case (diesel)

4.2 The second case of electric trucks

In this case, two trucks were needed as well. Total consumed energy, total distance, needed time for the process, and initial weights for each truck are presented in Table 5. Execution of the whole code is 13.95 s. Also, the total energy and distance for a random solution are mentioned.

Figures 5 and 6 show the actual routes for the optimized solution and random solution of this case. Red and blue colors are used to distinguish each truck's route.

Table 5 Results of electric trucks case

	Total energy (kWh)	Total distance (km)	Time (min)	Initial weight (Truck 1)	Initial weight (Truck 2)
Solution 1	**289.8513**	**24.7695**	**45.7**	**217**	**85**
Solution 2	326.82914	28.42226	42.4	187	115
Solution 3	298.91565	25.31579	39.8	208	94
Optimized solution	**289.8513**	**24.7695**	**45.7**	**217**	**85**
Random solution	707.68439	59.83013	-	-	-

Figure 5 Optimized solution for the second case (electric)

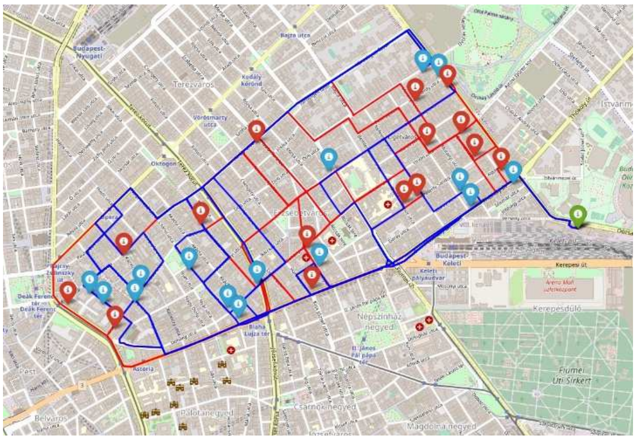

Figure 6 Random solution for the second case (electric)

5 Discussion and further research

The results showed a big difference between the optimized and random solutions. The random solutions in Figures 4 and 6 showed numerous overlaps in the selected routes, which explains why there is a raise in their results compared with the optimized solutions. Figures 7 and 8 express the differences for calculated total energy and distance where OS refers to the optimized solution and RS refers to the random solution.

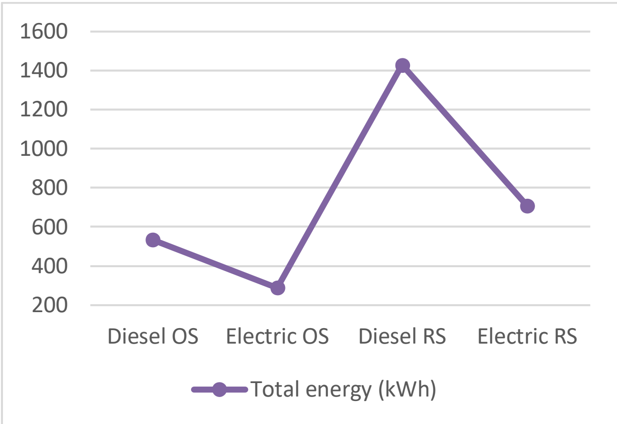

Figure 7 Calculated total energy

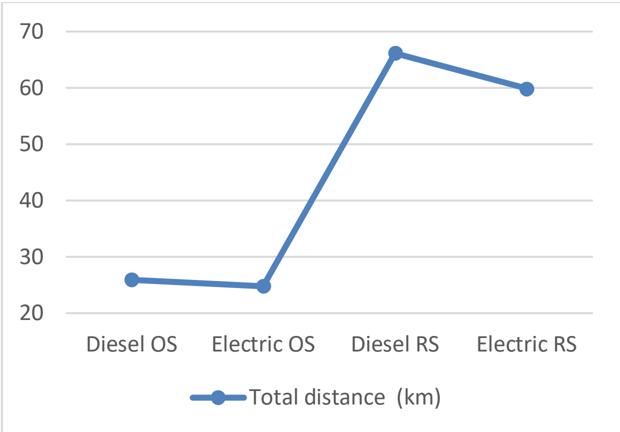

Figure 8 Calculated total distance

The results express two aspects to be compared. The first is the optimization efficiency of GA with the random solution comparison. The results expressed minimizing the total energy as 37.3% and 40.95 % compared to the random solution for diesel and electric cases respectively. Also, the results expressed minimizing the total distance as 39.2%

and 41.4 % compared to the random solution for diesel and electric cases respectively. Second, comparing the diesel and electric cases efficiency. The results expressed minimizing the total energy as 54.26% in the electric case compared to the diesel one. However, in the total distance, the results were very similar.

GA algorithm showed high efficient results in the optimization of this case, especially considering the applied upgrade where 3 solutions were done at the beginning to have a higher chance to exclude any possible local minimum points. The execution time is relatively acceptable since it will be done before the beginning of the process. However, even with conceding real-time updates, new runs to calculate updated routes are possible considering that it takes about around 15 seconds to reach the results for 30 location cases. The electric trucks showed a very positive impact on energy reduction, which supports adopting them widely in reality. However, possible challenges to this adoption may happen, therefore, analyzing real-life cases of electric truck use is interesting to find out the accrued trouble. The designed system tackled the last mile supply system, RL operations in city logistics, analysis of collected data, vehicles' actual real routes, energy optimization, and time window. By using actual real routes, further realistic and practical results were ensured.

Possible further research on this topic is recommended in three directions. The first direction, calculating accrued emissions since the emissions reflect directly on the sustainability aspect with considering the expected footprint difference between the electric and diesel truck. The second direction, since the optimization process does not have a limit to stop at, refinements in the presented mathematical model and the used GA algorithm structure are possible to be researched. Also, using hybrid algorithms is possible to be investigated as they showed promising outcomes in different cases [20]. The third direction, analyzing real-life case studies that use electrical trucks takes special importance as it is possible to analyze and find out unexpected problems.

6 Conclusion

Within this paper, last mile supply system within urban areas with a focus on the goods' delivery and collection tasks was presented. The model design was described, optimization mathematical modeling was detailed, and a case study to investigate the impact of using diesel and electric trucks on energy efficiency was solved. After an introduction and theoretical background that included a brief literature review, the designed system and used methodology were described. The designed system incorporated cloud computing, real routes of vehicles, analysis of collected data, energy consumption optimization, and time windows. Also, a mathematical model was developed with the aim of optimizing the total energy consumption. Real thirty locations in Budapest in the VII district were described and used as a case study for finding the solutions of the optimized taken routes and energy consumption by the genetic algorithm for both diesel and electric trucks. In the end, the results were analyzed and compared against a random solution to clarify the presented optimization's effectiveness.

The results expressed two aspects. First, regarding the optimization efficiency of GA with the random solution, results expressed minimizing the total energy as 37.3% and 40.95 % compared to the random solution for diesel and electric cases respectively. Also, the results expressed minimizing the total distance as 39.2% and 41.4 % compared to the random solution for diesel and electric cases respectively. Second, regarding the diesel and electric trucks' efficiency, the results expressed minimizing the total energy as 54.26% in the electric case compared to the diesel one. However, in the total distance, the results were very similar.

Depending on the achieved results, the authors recommend the adoption of electric trucks in the city center for their positive impact on the environment by saving spent energy. Also, optimization is widely used in transportation and logistics, however, raising the efficiency of the used optimization method next to widen the tackled data like including reverse logistics in the tackled system is highly recommended. This study's limitations include the following: first, using a single objective function while there is a possibility to use multi objectives optimization that would make the model more complicated but with further details and consideration for reality. Second, GA has many parameters to be specified while there is a possibility for more efficient parameters including the iteration number. Third, assumptions with average numbers were used to analyze the trucks' tasks. It is possible to use other types of trucks with more detailed specifications. Fourth, while the case study in this paper counted on real locations in Budapest, many assumptions and considerations were used as well. Finding a real case where electric trucks are used would be interesting to collect and analyze real data regarding the trucks and goods.

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Review process

Single-blind peer review process.