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Genetic algorithm approach to asymmetric capacitated vehicle routing: A case study on bread distribution in Istanbul, Türkiye

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A B S T R A C T

Conveying the products to the customers under optimized circumstances is as crucial for the companies as the production itself. One optimization strategy to consider is transportation with the minimum quantity of vehicles and the selection of courses with the minimum distance between the locations. In other words, it is the examination of the solution to the Vehicle Routing Problem (VRP), particularly the Capacitated VRP (CVRP), which is a more realistic modelization approach. For businesses that perform distribution to customers frequently, such as management work with the coordination of daily distribution, finishing the distribution on time is of great importance. In big cities with complicated roads and many dropping points, this can be achieved by benefiting from the systematic modeling of the CVRP. In this study, the delivery network investigation for one production facility of the Istanbul People's Bread positioned on the Asian side of Istanbul, Türkiye that distributes three times a day will be the focus of interest. The corresponding Asymmetric CVRP (ACVRP) for the facility network and 215 bread-selling buffets with authentic driving distances will be solved with the Genetic Algorithm (GA), and an optimized transportation network will be presented.

1. Introduction

The Industrial Revolution initially brought machinery into professional life, and subsequently, technological advancements made it possible to place machines in everyday life. While technology is a tremendous advantage in daily routines and workplaces, unfortunately, harm has emerged from its wrongful use. The goal of the technology is to make life easier, yet there is a worthwhile possible side consequence of environmental damage.

In the first stages, coal was the primary source of power. However, coal is not eligible for recycling, and it has also become among the sources of air pollution. Over time, electricity for local utilization and gasoline for transportation greatly took the place of coal. Millions of personal automobiles, buses, transportation-oriented vehicles, motorbikes, and trucks traveling by gasoline go out into traffic, and their numbers rise every day. For many years, gasoline has been regarded as the fuel for an extensive number of vehicles and indispensable machinery. Even though hybrid vehicles run by both gasoline and electricity, or purely electric vehicles now have their place in the automobile industry, they are not as popular as the fueled ones.

It might not be practicable to limit vehicles in traffic, but unnecessary overuse of commercial vehicles may be decreased. Shipping vehicles are obligated to navigate until they stop by every location marked by the employer. Navigation applications effortlessly offer routes when traveling from one site to another if the first point is the start and the other is the end. If there are additional stops, a few points may be added to the navigation system for the service. Nevertheless, in order to add stops, their sequence is input determined by the driver, not the software. Another complication is that the number of marking points is limited, thus technically unsuitable for commercial drivers. When this is the case, a more thorough and professional inquiry into the transportation routes appears to be the logical choice for the selection of courses.

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The successful analysis of city networks is the key point of the transportation sector with various aspects. The investigation is mainly about the infrastructure of the area detailed by the roadways eligible for vehicles. There are many drivers in traffic who are occupied with delivering goods taken from distribution point(s) to their destination(s) throughout the day. Evaluation of the distances between the locations is a favorable perspective for the purpose of transportation optimization. The assignment of the optimal routes, such as the distance minimization of the vehicles for the task of transmission, is a subject of inquiry for operations research. By reducing the cruise length of the vehicles, numerous positive outcomes will be eligible, such as visitation to more locations in less time, reduction in the use of fuel and consequently expenses, gas emissions caused by the vehicles, attrition at the engines of the vehicles, traffic density are the profits for the overall framework. As for the drivers, fatigue levels or anxiety about falling behind the schedule are important human factors that require attention since they may have an effect on traffic accidents. In this matter, the optimization is not just about the profit of the companies, but it is more about eco-policy, sustainability, and safety.

This research investigates the optimization of the route from a bread factory in the management of Istanbul Metropolitan Municipality to 215 shops in Istanbul, Türkiye. The factory is located in Cevizli, Kartal (Asia, Istanbul), and the nodes are all placed in Istanbul (Asia). The model of the ACVRP with the actual driving distances between the nodes has been constructed accordingly. Since a deterministic solution requires excessive time, a metaheuristic algorithm of the GA has been determined as the solution approach to the model. The addressed issue deals with three times a day delivery. With optimization of the routes, it has been estimated to optimize the transportation time, cost, and density of the traffic. As a result, from the angle of environmental benefit, it has been aimed to be sustainable and environmentally friendly by reducing the carbon footprint from the exhaust and minimizing unrecyclable fuel consumption.

The rest of the paper is constructed as follows. Section 2 provides a comprehensive literature review for CVRP, GA, and a combination of the two, respectively. Section 3 presents the basis of the ACVRP and the assumptions for the formulation followed by the mathematical model. Section 4 gives the preliminary information for the GA and required genetic operators. Section 5 is the original part of the study, and it expresses the real-world application denoted as ACVRP of the Istanbul People's Bread Company. Lastly, Section 6 discloses the outcomes of the research that were attained.

2. Literature Review

2.1. (Capacitated) VRP

The idea of optimization of the distribution network was initially added to the literature by Dantzig & Ramser (1959) as the problem of truck dispatching. The problem is designed as the transportation of all products from a central initial depot to destinations with the least distance route. Later, it has been referred to as the VRP. Clarke & Wright (1964) proposed that the VRP is a linear transportation problem that should be optimized and placed within the purview of operations research. This novel type of optimization problem has become progressively noteworthy over time. Afterward, this problem is modified with the extra condition of (equal) capacity for the identical vehicles in terms of validity and investigated as CVRP (Toth & Vigo, 2002). Laporte et al. (1986) examined the CVRP using an asymmetrical distance matrix and devised a deterministic approach. Laporte (1992) presented a review study for deterministic and heuristic methods that operate to solve the VRP. Savelsbergh & Sol (1995) studied the attributes of a standard VRP and surveyed various problem classes and solution approaches.

Chen et al. (2021a) conducted research on logistics for a Chinese e-commerce company with the use of the CVRP. Ma et al. (2021) handled the route optimization problem for the service of electric vehicles in their study for autonomous electric vehicles. Zhou et al. (2021) built a mathematical model with mixed integer linear programming and applied it to solve an electric VRP of an e-commerce company in China. Alesiani et al. (2022) utilized the tabu search approach to optimize large-scale CVRPs. They offered a method for finding a near-optimal solution or a solution that may be used as an initial point in the search for the ideal solution. Dubois et al. (2022) investigated the flood disaster problem and how the CVRP might help to optimize it for rescue vehicles. Ragab et al. (2022) worked on optimizing the route for drones with the smart city concept. Wu & Lu (2022) suggested a CVRP method incorporating demands without splitting. Zhang et al. (2022) showed the generated models and classifications specified for the VRP and the solution methodologies devised. Akin Bas & Ahlatcioglu Ozkok (2023) addressed a CVRP based on a fractional objective in terms of cost/load, and they concentrated on reducing the environmental impact of the vehicles. Damião et al. (2023) examined the CVRP approach with multi-depot variations using a methodology known as the branch, cut, & price. Golden et al. (2023) proposed a novel type of VRP, which they call rendezvous VRP, and presented its mathematical expression. They illustrated the problem with a modified heuristic algorithm on their designed tests. Horng & Yenradee (2023) presented a strategy for small and medium enterprises in terms of conducting a detailed delivery network. Souza et al. (2023) developed a hybrid framework that combines differential evolution and local search techniques for the solution of CVRP. They reached eminent results with their proposed approach. Tayachi & Jendoubi (2023) studied the green VRP that considers fuel consumption optimization and applied it to a VRP in Tunisia. Cai et al. (2024) examined the Multi-Objective (MO) VRPs involving time windows. Karels et al. (2024) proposed an improved branch & bound algorithm for a thorough investigation of transportation services involving the VRP. Lera-Romero et al. (2024) presented a branch, cut & price approach to solving the electric VRP specified by time windows. For more detailed references, review studies of Tan & Yeh (2021), Endler et al. (2023), and Ni & Tang (2023) may be examined.

2.2. GA

The main branches of optimization theory can be classified as classical mathematical programming, statistical and stochastic methodologies, and modern techniques. The GA, a commonly benefitted modern optimization technique, which was the proposition of Holland (1975), is of the modern method class. The biological sense of natural selection and evolution are the core logic mechanisms of the GA. The GA is a search strategy based on iterative optimization shaped by processes similar to biology and is successful in complex circumstances, while conventional techniques seem inadequate (Goldberg, 1989). Mühlenbein et al. (1991) utilized the GA in order to find the local optimum point for continuous functions and proposed the parallel GA for this occasion. Whitley (1994) published a study intended to be a tutorial for the GA. Osyczka & Kundu (1995) introduced a GA approach to solving the MO optimization models by aggregating the objectives into one objective. Chu & Beasley (1997) suggested a GA framework that solves the assignment problem in a generalized form, and in their examinations, they reached results that are incredibly close to the optimality. Deb et al. (2002) presented a novel algorithm called nondominated sorting GA II that has the infrastructure of solving MO optimization problems with the elitist GA approach. This methodology has attracted outstanding attention and is still being studied by many researchers.

In time, GA has been a popular tool for the examination of many problem types. Bărbulescu et al. (2021) assessed the soil types by clustering them with the k-means algorithm and then classifying them by applying the GA. Chen et al. (2021b) employed the GA as a data mining technique for the image recognition context. Gümüş et al. (2021) studied the minimization of power loss and used the GA as the instrument for this problem. Yasmeen et al. (2021) performed their GA-based research on the diagnostics of diseases that emerge from the citrus. Zagan et al. (2021) investigated the approximate time required to repair the ships. They utilized the GA to calculate the coefficients in their model of linear regression. Dang (2022) presented a novel approach with the assistance of a GA for a mobile education framework. Karambasti et al. (2022) applied the GA for optimal house design modeling under the green concept. In the research of Lopez-Rincon et al. (2022), they chose to use the GA for the art of music composition. Sathya et al. (2022) examined the biomarker genes with a GA in order to diagnose and plan the treatment for the cancer type a patient suffers from. Yao & Xu (2022) evaluated the English text documents through the GA to establish a system for text analysis. Luo et al. (2023) investigated the buildings in terms of green energy. They regarded some energetic factors via GA and considered the issue of optimization for these factors. Mahlous & Mahlous (2023) analyzed the demands of the students with the aim of giving a chance to as many university students as possible to enroll in their desired classes. MazhariSefat & Hosseini (2023) worked to build a security system for computer viruses detected with the help of the GA. Wang et al. (2023) conducted research to schedule the traffic using the transit network and GA. Krishna & Rao (2024) concentrated on the factors affecting blood pressure and developed an optimization program with a GA to regulate the blood pressure of the patients. For a comprehensive review, the survey of Katoch et al. (2021), which widely reviewed the works in the literature regarding the GA, is recommended.

2.3. VRP with GA

The complexity degree of the CVRP extends considerably as the total quantity of nodes increases. Henceforth, it is referred to as an NP-Hard classified problem formulation of optimization theory. Modern procedures attracted scholars to the pursuit of near-optimal solutions for these kinds of complicated and sometimes even impossible-to-solve problems. A high number of research studies in the literature have incorporated GA for combinatorial problems in the manner of VRPs. Goldberg & Lingle (1985) proposed the partially matched crossover operator for the solution of the problem types encoded by permutation form. Davis (1985) presented the order crossover as an alternate for the crossover operator of the permutation encoding. Later, another crossover type for the permutation problem, which they called the cyclic crossover, was developed by Oliver et al. (1987). Kargupta et al. (1992) examined the permutational classified models, which they called ordering GA, and the crossover operators compatible with this problem type. Baker & Ayechew (2003) proposed the GA to solve the VRP and conducted a comparative test with the benchmark instances. Prins (2004) observed a gap in the literature for the VRPs that used the GA as the solution strategy and submitted research that indicated the potential of the algorithm by solving some benchmark sets.

Comert and Yazgan (2021) presented a multi-stage methodology works by the construction of a model with ant colony optimization, GA, and artificial bee colony algorithm and then transforming one lengthy traveling salesman problem into a CVRP. Karakatič (2021) applied the GA to address a challenging CVRP with nonlinear recharge periods that correspond to time windows. Sajid et al. (2021) provided a novel strategy for the CVRP and demonstrated its efficiency using an instance that included a symmetrical distance matrix. Hvattum (2022) devised a GA that employs the order crossover operator regarding CVRP adaptation. Lesch et al. (2022) investigated the ant colony optimization and GA for the VRP in view of the time requirements during the touring sites. Sbai et al. (2022) adopted an actual-world scenario of a postal facility in Tunisia by approaching the issue within the framework of a CVRP and assessing it with the aid of a variable neighborhood search-associated GA. Zhu et al. (2022) used a two-phase strategy of fuzzy clustering and GA to determine a solution regarding the CVRP. Ahmed et al. (2023) focused on the efficiency crossover operator of the GA designed for the permutation encoding to solve the CVRPs. Ansari & Alnajjar (2023) researched an issue with connectivity with the intent of establishing the optimal transmission pathway. The researchers employed the GA to handle the problem and compared the results with deterministic outcomes. Mrad et al. (2023) comprehensively investigated transportation for location, allocation of warehouse, and VRPs. They tested the success of the proposed instances by results from the benchmark datasets. Ozcetin et al. (2023) studied a sanitary problem through a mathematical framework for the decision of optimal vehicle attributes and a GA to work out the VRP. Wang (2023) implemented a mixed integer programming problem for an unmanned aircraft fleet along with a GA to tackle the complicated challenge of VRPs. Zhao et al. (2023) hybridized the GA with a large neighborhood search and made a comparison with the standard GA. They presented their method by solving a real-life application for an airport in Beijing.

3. Vehicle Routing Problem

A VRP can be defined as the search for the optimal transportation route for the products from a distribution center (depot) to customers (destinations) with a fleet of equivalent vehicles. This problem type generally has the following assumptions (Caccetta & Hill, 2001):

- Each of the routes must include the depot.
- The product and the demand of the customers are certain and predefined, and only a single kind of product will be distributed.
- Each customer must be visited by exactly one vehicle, and this single vehicle will supply the requested demand.
- All of the vehicles will be tasked to go out for only one tour.
- The objective is the minimization of the total distance of all roads to be driven.
- The model transforms into the CVRP if identical vehicles also have equal capacity constraints.
- The total demands of the customers cannot surpass the sum of the full capacity of the vehicles.

Let a graph be defined as $\mathcal{G} = (\mathcal{N}, \mathcal{A})$. Here, $\mathcal{N} = \{0,1, \ldots, \nu\}$ represents the nodes set of one depot ν destinations with $\nu + 1$ elements where 0 describes the depot and 1 to ν describes the customers and $\mathcal{A}$ denotes the arcs between the nodes. A cost matrix $[\delta_{ij}]_{(\nu+1)\times(\nu+1)}$ is required to be evaluated between each node. Generally, the costs are the (non-negative) distances between the nodes. The cost of the route for node $i \in \mathcal{N}$ to node $j \in \mathcal{N}$ is defined by the arc $(i,j) \in \mathcal{A}$, and it provides the element δ_{ij} at the cost matrix. Moreover, the condition of $i \neq j$ needs to be taken into account. If $i = j$, this equality implies an inconsiderable travel from the node to itself. Thus, the cost δ_{ii} is of an impracticable route, and it takes place at the matrix with a symbol of illegal move $-$ or ∞. In other words, the diagonal of the cost matrix is the impossible route. If for all i, j, $\delta_{ij} = \delta_{ji}$ this indicates a symmetric matrix. However, if for at least one i, j this equality does not hold, i.e., $\mathcal{G}$ is a directed graph, the matrix $[\delta_{ij}]_{(\nu+1)\times(\nu+1)}$ is called an asymmetric matrix. For the real-world cases, if the distances construct the cost matrix, the matrix is mostly asymmetric since some roads are possibly one-way directions, and hence, the distance varies (Toth & Vigo, 2002).

The mathematical formulation of the ACVRP is described as follows (Toth & Vigo, 2002):

$$\min \sum_{(i,j)} \sum_{k=1}^{\mathcal{K}} \delta_{ij} x_{ij}^{k}, \qquad (i,j) \in \mathcal{A} \tag{1}$$

subject to

$$\sum_{k=1}^{\mathcal{K}} x_{ij}^{k} = y_{ij}, \qquad \forall i, j \in \mathcal{N} \tag{2}$$

$$\sum_{i=0}^{\nu} y_{ij} = 1, \qquad \forall j \in \mathcal{N} \setminus \{0\} \ \text{ and } \ \sum_{j=0}^{\nu} y_{ij} = 1, \qquad \forall i \in \mathcal{N} \setminus \{0\} \tag{3}$$

$$\sum_{i=0}^{\nu} y_{i0} = \sum_{j=0}^{\nu} y_{0j} = \mathcal{K} \tag{4}$$

$$\sum_{i=1}^{\nu} \sum_{j=0}^{\nu} \gamma_i x_{ij}^{k} \leq \rho, \qquad \forall k = 1, \ldots, \mathcal{K} \tag{5}$$

$$\sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{S}} y_{ij} \leq |\mathcal{S}| - 1, \qquad \emptyset \neq \forall \mathcal{S} \subseteq \mathcal{N} \setminus \{0\} \tag{6}$$

Here,

- graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ is defined as above,
- $\mathcal{K}$ specifies the number of vehicles,
- x_{ij}^k is the binary decision variable denoting whether if the vehicle k uses the arc (i, j),
- y_{ij} is the binary decision variable denoting whether if the arc (i, j) is at the solution or not,
- depot is described with node 0,
- γ indicates the demand for the product for each customer,
- ρ is the limitation of capacity for a vehicle,
- (6) is the constraint for the elimination of subtours.

4. Genetic Algorithm

A GA begins with the encoding technique, which is determined by the classification of the decision variable for the optimization model to be addressed. As the variables have been transformed in accordance with the suitable GA, a population is generated at random. Hence, the iterative phase of the technique initiates. Iterations are carried out via selection, crossover, and mutation processes (Kramer, 2017). The population improves with regard to the specified convergence condition(s) of the methodology following each round of iteration. Subsequent to every iteration, the convergence of the best individual in the population must be assessed. If the requirement is fulfilled, a result that is expected to be near-optimal ought to be reached (Sivanandam & Deepa, 2008). Table 1 illustrates the flow, and Figure 1 depicts the flowchart of the GA (Affenzeller et al., 2009).

Table 1
Flow of a standard GA

Step 1	Initiate population
Step 2	Calculate Fitness Values (FVs) for population
Step 3	Choose parents from the population (Selection)
Step 4	Generate children (Crossover)
Step 5	Transfigure children with minimal texture (Mutation)
Step 6	Calculate FVs for children
Step 7	Change population
Step 8	If the end criterion/criteria is/are not satisfied, go to Step 3
Step 9	End

4.1. Genetic Operators

4.1.1 Roulette Wheel Selection

The basic concept of this strategy is to assess the selection possibilities of the individuals in proportion to their FV. The selection probability of an individual is the proportion of the FV of the individual to the overall FV of the population. Considering these parameters, each individual is allocated a proportionate Roulette Wheel (RW) slice. The selection of parents for the next generation is performed for a population of η individuals by rotating the RW η times. At every spin, the individual indicated by the pointer has been determined as the winner to take place in the parent pool (Sivanandam & Deepa, 2008).

4.1.2 Stochastic Universal Sampling

This approach proposes rotating the RW basically 1 time to perform a selection for a population of η individuals utilizing η points at identical distances from one another. However, the probability of selection handled is the same as RW selection. As an outcome, η individuals will be elected all at once to constitute the parent pool. Therefore, it is attempted to avoid the disappearance of individuals with high FV due to an entirely unfortunate selection (Sivanandam & Deepa, 2008; Mitchell, 1998).

4.1.3 Tournament Selection

The population in question is split into τ groups, where τ is the size of the tournament. The individual with the greatest FV in each division will be declared the tournament champion. As a result, the tournament champions of each group will be chosen for the parent pool (Sivanandam & Deepa, 2008; Affenzeller et al., 2009).

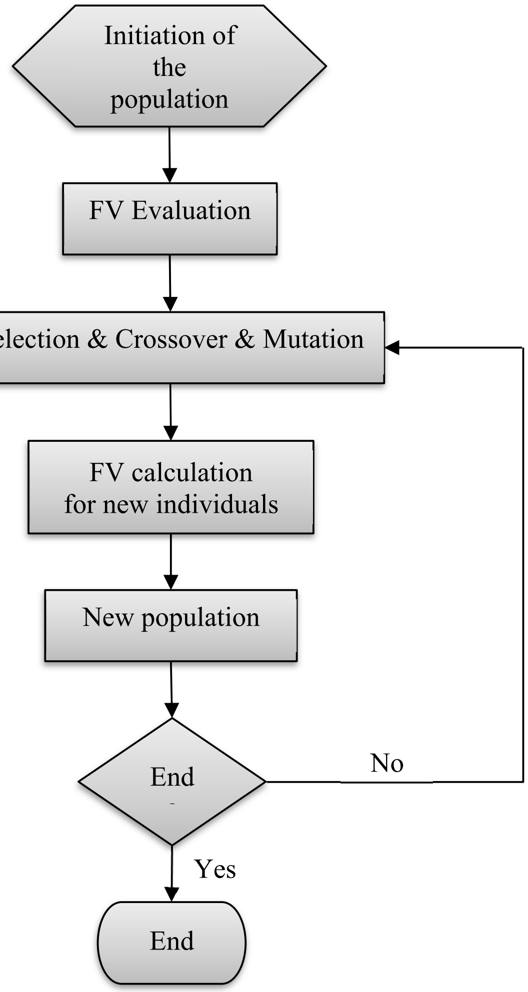

Fig. 1. Flowchart of standard GA

4.1.4 Rank Selection

The individual with the worst FV is placed at the position 1 in rank selection. For a population of η individuals, all individuals in the population are ordered in ascending order according to their FVs, and the individual with the overall FV is allocated at the position η. Then, the RW technique is applied to create the parent pool. Therefore, the diversity of the individuals in populations with a clear distinction between FVs is maintained (Sivanandam & Deepa, 2008).

4.1.5 Order Crossover

The order crossover operator has been developed with the concept that the order of genes is more prioritized than the location of genes. Initially, two crossing points are assigned to employ the operator. The function of the operator is that Child 1 acquires the elements from Parent 2, and Child 2 correspondingly receives elements from Parent 1 in between the crossing points. The components of Child 1 are then filled in the same sequence as Parent 1 without duplication as possible, and Child 2 is formed in the same manner (Affenzeller et al., 2009).

4.1.6 Inversion Mutation

The inversion mutation provides that the genes on the chromosome between a pair of genes chosen as the mutation point will be repositioned in the reverse sequence (Sivanandam & Deepa, 2008).

5. Istanbul People's Bread

5.1 Preliminary Information

Two types of bread cookers exist in Istanbul, Türkiye. One is the bakeries of the private sector, and the other is the people's bread company affiliated with the Istanbul Metropolitan Municipality. The Istanbul People's Bread company makes daily production and operates every day except Sunday. They distribute bread to their associated shops three times a day. The company, which was established in 1977, provides the demands of approximately 10% of the population in Istanbul (Istanbul People's Bread). That is 1.6 million people, considering the total population of the metropolitan city is roughly 16 million. The company runs with a staff of over 600 people and has almost 3,000 shops to serve the citizens in Istanbul. There are four production facilities; three are on the European side of Istanbul, and the other one, the Cevizli factory, which is the focus of this research, is in the district of Kartal, located on the Asian side of Istanbul. There are 215 shops in Istanbul, Asia, and all of the distributions to these shops are supplied from the Cevizli factory (Istanbul People's Bread).

5.2 Collection of the Data

In order to construct an ACVRP model, the requirements are the cost matrix, demands, and the number of vehicles together with their (equal) capacity.

5.2.1 Cost Matrix

The objective of the problem has been defined as the minimization of the total distances. First, the locations (coordinates) of the production factory and the shops have been reached from the Istanbul Metropolitan Municipality open source website (Istanbul Metropolitan Municipality). Then, to obtain the driving (real) distances of the destinations, Python package software and OpenStreetMap library have been utilized to form the asymmetric distance matrix with the size of 216×216. The names of the shops are presented in Table 2, and the locations of the shops over the map are illustrated in Fig. 2. However, since the distance matrix is enormous enough to fit the page, it could not have been involved in the paper.

5.2.2 Demands

The demands of the shops have been associated with the population of the area where the shop is located. For this, the population of each district and the neighborhood of the corresponding district have been investigated. The required data have been acquired from the Turkish government open data source (Turkish Statistical Institute). Then, it has been considered that the Cevizli factory has the capacity to bake 1,200,000 loaves of bread daily. Since the distribution is three times a day, it has been regarded that each distribution consists of 400,000 loaves of bread.

The population of each district has been proportioned to the population in the Asian side of Istanbul. Similarly, the population of each neighborhood has been proportioned to the proportion of relevant districts. Eventually, the ratio calculated for each is multiplied by the total loaf number of bread, and the demands for each shop are estimated. If there is more than one shop in a neighborhood, the proportions are arranged as if they have equal demands, and the total of these demands matches the ratio obtained for that neighborhood. The demands for each shop are depicted in Table 3. It should be noted that the loaves of bread are carried by cases that each can fit in 40 loaves of bread, and the demands are described in the form of case quantities. Thus, instead of 400,000 loaves of bread, 10,000 cases are the capacity of the factory in question and hence assumed to be the total demand of the shops.

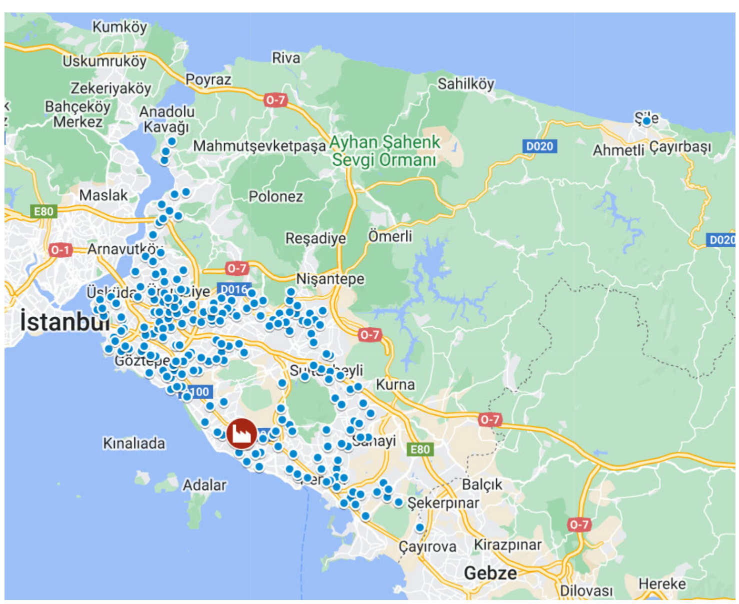

Fig. 2. Shops of Istanbul People's Bread in Istanbul (Asia) over the map

Table 2
The shops of Istanbul People's Bread in Istanbul, Asia

1 Sancaktepe Yunus Emre	55 Küçükbakkalköy Merkez 2	109 Tarih	163 Fikirtepe Altınsu
2 Ümraniye Akdeniz	56 Şile Merkez	110 Maverapark	164 Kuyubaşı
3 Barbaros 2	57 Acıbadem	111 Yavuztürk	165 İkbaliye
4 Aydınlı 2	58 Sultanbeyli Bahçe	112 Kirazlıtepe	166 Kızıltoprak
5 Ataşehir Bağkur	59 Ümraniye Kurtuluş	113 Rüzgarlıbahçe	167 Ziverbey
6 Aydınlı Bahçeler	60 Osmangazi	114 Beykoz Parkı	168 Sahrayı Cedit
7 Kurtköy Kanarya	61 Mustafa Kemal	115 Beykoz Soğuksu	169 Gökay
8 Ataşehir Barbaros	62 Sancaktepe Onur	116 Ortaçeşme	170 Türkiş Merkez
9 Atakent	63 Barajyolu	117 Pendik Üçevler	171 Ataşehir Yeditepe
10 Paşabahçe Okul	64 Esenevler	118 Bosna Parkı	172 Fındıklı Merkez
11 Merve 2	65 Ümraniye Hastane	119 Kartal Esentepe	173 Ataşehir Fidan
12 İnönü	66 Kadıköy Söğütlüçeşme	120 Leylak	174 Küçükyalı
13 Ferhatpaşa 2	67 Ferhatpaşa	121 Atalar	175 Bostancı İskele
14 Safa	68 İnkılap	122 Şenesenevler	176 Kayışdağı Kar
15 Çubuklu Vatan	69 Esenler	123 Maltepe Koruma	177 Yeşilyamaç
16 Rasimpaşa	70 Asya	124 Baki	178 Bostancı Köprü
17 Yenişehir	71 Cemil Meriç	125 Aydınlı Merkez	179 Maltepe Park
18 Pendik İstiklal	72 Altıntepe	126 Tuzla Emlak	180 Fidanlık
19 Çubuklu	73 Rasathane	127 Esenyalı Fatih	181 Ataşehir Su Deposu
20 Taşkın	74 Bayraktar	128 Piri Reis	182 Köşem
21 Başıbüyük	75 Güzelyalı	129 Şifa Kiptaş 2	183 Çiftlikyolu
22 Ertuğrul Gazi	76 Parseller	130 Kartal Metro	184 Topağacı
23 Necip Fazıl	77 Yayalar	131 Plevne	185 Talatpaşa
24 Dudullu Meydan	78 Doğuşkent	132 Aydınlıköy Toki	186 Anafartalar
25 Battalgazi	79 İçmeler Merkez	133 Küçükbakkalköy Merkez	187 Ümraniye Site
26 Koşuyolu 2	80 Kavacık	134 Zümrütevler	188 Mevlana
27 Petrol İş	81 Çamçeşme	135 Cevizli Fabrika	189 Kozyatağı Metro
28 Fıstıkağacı	82 Göksu	136 Cumhuriyet	190 Ümraniye Merkez
29 Salacak	83 Kavacık Çiftlik	137 Pendik Mostar	191 Marmara
30 Kayışdağı Rumeli	84 Hekimbaşı Çiftlik	138 Orhangazi	192 Adem Yavuz
31 Yeni Mahalle	85 Ümraniye Atay	139 Esen	193 Ümraniye Sultan
32 Abdurrahmangazi 1	86 Fetih	140 Üst Kaynarca	194 Ümraniye Tanzim
33 Koşuyolu	87 Nurol	141 Yakacık	195 Ümraniye Vatan
34 Abdurrahmangazi 2	88 Esatpaşa	142 Kartal Meydan	196 Soğanlık
35 Şeyhli	89 Ferah	143 Hürriyet Merkez	197 Barışyolu
36 Tugayyolu	90 Üsküdar Güzeltepe	144 Pendik Toki	198 Gümüşpınar
37 Ümraniye Tantavi	91 Ünalan Merkez	145 Kurtköy	199 Dudullu Merkez
38 Çekmeköy Mimar Sinan	92 Pendik Bulvar	146 Çınar Park	200 Kemerdere
39 Mimar Sinan 2	93 Horon	147 Seyrantepe	201 Ulubatlı Hasan
40 Bulgurlu Metro	94 Sultanbeyli Hilal	148 Alt Kaynarca	202 Yıldırım Beyazıt
41 Ünalan 2	95 Sancaktepe Veysel Karani	149 Kavakpınar	203 Yenidoğan Dörtyol
42 Turgut Reis	96 Sultanbeyli Pelit	150 Kazasker	204 Kemal Türkler
43 Hamidiye	97 Demokrasi	151 Çiçekçi	205 Uğur Mumcu Meydan
44 Mecidiye	98 Kıbrıs	152 Çengelköy İtfaiye	206 Sarıgazi Merkez
45 Sultanbeyli Mehmet Akif	99 Taşdelen 19 Mayıs	153 Örnek	207 Uğur Mumcu
46 Merve	100 Soğukpınar	154 Bulgurlu	208 Madenler
47 Caferağa	101 Ortadağ	155 Üsküdar Meydan	209 Acısu
48 Merdivenköy	102 Soğanlık Metro	156 Cuma Pazarı	210 İkbal
49 Caddebostan	103 Maltepe Esenkent	157 Emniyet	211 Sevgi Parkı
50 Osmangazi 2	104 Çeşme	158 Bahçelievler	212 Tatlı Su
51 Sarıevler	105 Güllübağlar	159 Eğitim	213 Tavukçuyolu
52 Cevizli	106 Pendik Kaymakamlık	160 Kozyatağı	214 Uhut
53 Sarıgazi Okul	107 Manolya Site	161 Suadiye	215 Ihlamurkuyu
54 Sancaktepe Veysel Karani 2	108 Çengelköy	162 Kozyatağı Şakacı	0 Cevizli (Factory)

5.2.2 Vehicles

In terms of weight, each of the vehicles that the company uses to distribute is able to carry 4.9 tons. Considering that each loaf of bread is 250 grams, a truck has the capacity of 19,600 loaves of bread or, with regard to cases, 490 cases of bread. For the total quantity of demand, that is 10,000, at least 21 vehicles are necessary.

5.3 Solution of the ACVRP

To achieve the solution of the presented ACVRP model, a modified GA has been utilized via MATLAB package software. The GA has been applied in a laptop run by Windows 11 software, and 11th generation processor and 24GB of memory hardware. For the implementation of the GA, the size of the population has been selected as 128, the size of the parent pool has been determined as 16, and the replacement size has been chosen as 8. As for the operators, the convenient one among the four given selection operators has been employed, and order crossover has been the crossover strategy. Inversion mutation with the probability of 10% has been preferred as the mutation operator. The GA code has been executed many times to obtain a solution regarding the minimum requirement of 21 vehicles. All the attempts have failed, and the algorithm has diverged even with more restricted convergence conditions except for one try. Nevertheless, this solution was observed to have a worse objective function value than any solution obtained by running the program for 22 vehicles under the convergence criteria of at least 100,000 generations and stays unchanged at the best objective function value for at least 100,000 generations. The program has been tested for ten converging solutions, and the best objective values, elapsed times, and iteration counts are provided in Table 4.

Table 3
The demands of the shops

Shop	Demand	Shop	Demand	Shop	Demand	Shop	Demand	Shop	Demand	Shop	Demand
1	35	37	13	73	50	109	43	145	40	181	31
2	15	38	119	74	12	110	13	146	61	182	40
3	35	39	30	75	37	111	43	147	27	183	40
4	66	40	40	76	18	112	24	148	101	184	32
5	13	41	46	77	29	113	37	149	141	185	30
6	66	42	53	78	54	114	18	150	86	186	111
7	40	43	71	79	52	115	51	151	31	187	8
8	35	44	59	80	103	116	18	152	30	188	33
9	45	45	73	81	35	117	43	153	60	189	40
10	17	46	18	82	6	118	26	154	40	190	36
11	18	47	58	83	6	119	74	155	28	191	33
12	63	48	28	84	89	120	58	156	23	192	36
13	23	49	55	85	49	121	27	157	43	193	28
14	62	50	22	86	13	122	25	158	30	194	28
15	47	51	42	87	99	123	57	159	35	195	35
16	35	52	32	88	72	124	61	160	25	196	23
17	35	53	42	89	53	125	66	161	25	197	68
18	37	54	22	90	56	126	66	162	25	198	64
19	47	55	33	91	46	127	46	163	28	199	47
20	70	56	77	92	35	128	31	164	69	200	64
21	62	57	39	93	58	129	130	165	39	201	68
22	28	58	54	94	58	130	23	166	22	202	38
23	58	59	48	95	35	131	17	167	37	203	18
24	33	60	22	96	88	132	66	168	82	204	56
25	102	61	31	97	91	133	33	169	28	205	50
26	18	62	70	98	48	134	249	170	39	206	61
27	27	63	12	99	84	135	32	171	31	207	50
28	42	64	30	100	46	136	35	172	183	208	35
29	25	65	50	101	95	137	34	173	31	209	24
30	31	66	43	102	70	138	35	174	73	210	55
31	17	67	23	103	53	139	42	175	88	211	87
32	38	68	35	104	46	140	82	176	31	212	24
33	35	69	73	105	39	141	43	177	12	213	12
34	38	70	59	106	35	142	42	178	40	214	12
35	41	71	18	107	43	143	123	179	57	215	50
36	57	72	45	108	36	144	54	180	45		

Table 4
Objective values, elapsed times, and iterations for ten solutions

Solution	Objective value (meter)	Elapsed time (second)	Iteration
1	1,182,568.527	1,809.1454	334,597
2	1,220,059.187	1,679.9195	304,900
3	1,203,720.72	1,411.0974	255,048
4	1,197,192.321	1,515.6399	277,396
5*	**1,102,103.122**	1,854.3995	337,528
6	1,122,080.108	1,719.9279	311,849
7	1,152,646.083	1,386.6402	253,024
8	1,115,985.156	1,673.5229	304,410
9	1,147,543.142	1,761.6063	321,115
10	1,113,084.929	1,821.9520	331,406
Average	1,155,698.329	1,663.3851	303,127.3

From Table 4, it can be noticed that the fifth solution has the shortest length value and could be appraised as the solution to the problem. The model has been solved in an average of 1,663 seconds, approximately 28 minutes, and with an average of 303,127 iterations. While the number of iterations mainly depends on the size of the population and parents, not only the size of the ACVRP model, elapsed time affects the size of the model at most. For a 215+1 nodes model solved by 22 vehicles, an average time of under half an hour may commonly be regarded as fast enough. The route obtained from solution five has been presented in Table 5.

Table 5
The best route for the model

Vehicle	Route	Load (cases)
1	0→198→23→203→1→95→100→99→206→207→0	451
2	0→8→2→185→191→190→212→13→67→62→20→98→11→54→0	447
3	0→176→201→200→70→214→87→5→153→3→183→0	481
4	0→94→92→125→129→132→4→124→0	482
5	0→120→75→126→6→7→136→138→107→130→0	403
6	0→173→181→88→86→91→167→166→16→66→175→123→0	475
7	0→160→150→61→108→19→114→116→21→115→10→15→82→9→0	489
8	0→55→209→202→38→12→51→53→204→93→0	475
9	0→103→171→170→210→74→71→76→199→97→14→0	426
10	0→143→31→77→144→17→145→105→106→148→0	473
11	0→52→139→118→18→127→128→79→147→179→174→78→0	477
12	0→117→35→22→44→56→46→50→25→60→205→0	462
13	0→63→213→211→193→37→194→184→187→215→24→197→208→59→0	454
14	0→72→164→47→165→57→26→112→40→41→189→0	418
15	0→102→101→104→141→119→142→27→146→0	458
16	0→33→151→156→29→155→39→28→159→90→110→68→85→177→30→0	445
17	0→196→58→43→42→32→96→34→45→0	438
18	0→64→154→89→152→65→195→188→186→36→0	439
19	0→133→168→48→163→169→178→182→172→0	462
20	0→134→162→49→161→122→180→0	424
21	0→135→69→81→149→140→137→131→121→0	441
22	0→157→158→73→80→83→113→84→109→111→192→0	480

6. Results and Conclusions

In this research, a case study of ACVRP has been considered via the solution tool GA. The case in question is the distribution of bread from the factory to 215 shops with the objective of minimization of distance. The results showed that while it is possible to distribute 21 vehicles, it actually has a need for 22 vehicles. It has been presented that a problem with a considerably substantial size can be solved in less than half an hour. At the same time, even finding a solution is a matter of investigation for these types of complex optimization models. Eventually, GA reached a profitable route that was presented.

The operations research is about planning for the optimization of the models of real-life instances. Even when the objective function may seem to be about profit, it also serves as the optimal utilization of the sources. In some circumstances, such as working on the VRP, economic employment of the sources for businesses can be accounted for by avoiding from the sources of the world. The aim of this study is to optimize the routes for a company in charge of transportation of 1,200,00 loaves of bread by three times delivery a day. It is believed that the minimization of the distances can decrease the carbon footprint and gas emissions that the vehicles cause. By this means it significantly influences providing an eco-friendly application to management, as the sustainability of natural sources matters the most.

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