2020 International Conference on Electrical Engineering (ICEE)
September 25-27, 2020, Istanbul, Turkey

An Evolutionary Approach to Multiple Traveling Salesman Problem for Efficient Distribution of Pharmaceutical Products

Emre Kocyigit
Yildiz Technical University
Computer Engineering Department
Istanbul, Turkey
kocyigit.emre.30@gmail.com

Ozgur Koray Sahingoz
Istanbul Kultur University
Computer Engineering Department
Istanbul, Turkey
sahingoz@gmail.com

Banu Diri
Yildiz Technical University
Computer Engineering Department
Istanbul, Turkey
diri@yildiz.edu.tr

***Abstract*—Considerable growth of computer science has created novel solutions for variable problem fields and has increased the efficiency of available solutions. Evolutionary algorithms are quite successful in dealing with real-world problems that require optimization. In this article, we implemented a Genetic Algorithm that is well known evolutionary algorithm in order to provide an efficient solution for the Distribution of Pharmaceutical Products, which is a vital optimization problem, especially in situations such as a pandemic. The Multiple Traveling Salesman Problem approach was used to distribute pharmaceutical products as soon as possible. Moreover, we strengthened our proposal algorithm with 2-Opt Algorithm to get optimal results in earlier iterations. Different datasets from a library were applied to measure the quality of solutions and computation time. At the end of the work, we observed that our proposed algorithm generates successful solutions in an acceptable running time. This study will be extended with a new mutation concept as future work.**

Keywords—evolutionary algorithms, genetic algorithm, multiple traveling salesman, distribution of pharmaceutical products

I. Introduction

With the developing technology, all real-world problems have begun to be solved with the help of computers and the efficiency of the systems has started to be increased. After computers became an essential part of this World, company profits have been ascended and optimal solutions have been created. As the complexity of the World problems increases, standard approaches are not sufficient and sophisticated. Evolutionary Algorithms (EAs) come into play at this point. It brings a new perspective to problem solutions with untraditional optimization approaches and presents significant performance and efficiency augmentation. EA is preferred to acquire successful and productive solutions for various problem fields. For example, the Genetic Algorithm (GA), which is one of the EA, was used for green vehicle routing problem[1] .

Carrying out the distribution in optimal time is one of the major problem areas where Evolutionary Algorithms can be applied. Especially in the global crisis environment caused by the Covid-19 pandemic; the need for rapid distribution of medical supplies such as breathing apparatus, surgical masks, and hygiene materials such as disinfectants, diapers have emerged. In this context, we conducted a study that utilizes EA to distribute vital medical supplies as fast as possible.

In the following sections, first, the concepts of Traveling Salesman Problem (TSP) and Multiple Traveling Salesman Problem (MTSP), which form the basis of our work, were explained. Moreover, comprehensive literature review was conducted in this section in order to convey the background of our problem and approach. Secondly, our proposal system was detailed. After explaining experimental results in the fourth section, our paper was finalized with a conclusion and future works.

II. Background

A. Travelling Salesman Problem

TSP is the problem of finding the shortest route for a set of points, provided that all points are visited once. The starting point is also the endpoint of the route. Salesmen should keep the travel cost as low as possible while visiting these points. While each point in the TSP represents the locations that need to be visited, this approach can be adapted for many different problem areas. Multiple Travelling Salesman Problem (MTSP) is the situation in which the TSP is realized with more than one salesman. As the condition of visiting each point once is valid, there are more than one salesman performing the path. More effective and practical solutions can be provided with MTSP, especially when there are too many points that need to be visited for a single salesman. We also benefited from MTSP approach to create an optimal solution for the distribution of pharmaceutical products. Considering the real-life problems, MTSP emerges as a more practical approach than TSP. Figure 1 shows an MTSP example with one depot. One depot (the red one) represents the medical center that distributes products and it is both the start point and endpoint of the path.

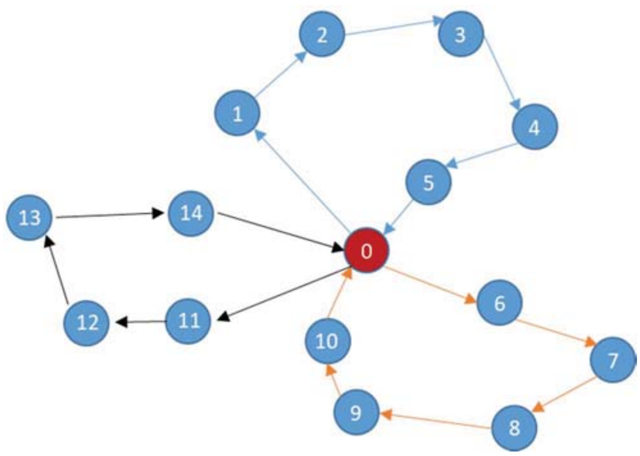

Figure 1. MTSP Example

B. Literature Review

We mentioned several algorithms and studies of literature that were used to solve MTSP in this section. Genetic algorithm was used in the solution of Multi UAV path planning problem depending on different constraints in various research [2]. Due to its availability on 2-dimensional space, Multi TSP is being a good solution about this type of problems. On the other hand, simulated annealing can also be used for solving this type of problem [11].

It was benefit from various heuristic algorithms that are frequently used in the solution of NP-Hard problems for MTSP. One of these algorithms is the ACO, which is also frequently used to solve TSP efficiently. In the study by Kencana et al. used Ant System to solve MTSP and stated that the increase in salesperson had a significant effect on working time but not a significant effect on minimum total distance [3]. As another example, Pan Junjie et al. also tried to solve MTSP with ACO algorithm by using some standard data sets from TSPLIB. It has been stated that it does not give very successful results, especially in large scale data. As a result of the work, they also made a comparison with the Modified GA (MGA), and stated that ACO could not give the most successful results compared to MGA, but they achieved competitive results[4].

In addition, GA, Combined K-Means/Nearest Neighbor and Random Cluster/Tour Algorithms were executed in the first phase in order to efficiently solve Multi Travelling Salesman Drone Problem, which is an extension of MTSP and also examined the effects on the further stages of the algorithm. GA gave better results within a reasonable running time and had a lower standard deviation for different data sets. [5] On the other hand Carter and his friend, while using the GA to solve MTSP, have tried to achieve more successful results by presenting a new approach to crossover, one of the critical operators of the GA[6].

MTSP is not just about generalizing the TSP. Considering the real-life problems, more efficient results can be obtained with MTSP. For this reason, hybrid approaches have been adopted in some studies. For example, Chao Jiang et al. tried to solve MTSP using a hybrid algorithm named "ant colony-partheno genetic algorithm". In the study, in which comparative experiments were conducted with Artificial Bee Colony and Invasive Weed Optimization algorithms, it was stated that the hybrid algorithm was more successful and efficient enough in large-scale MTSP than other algorithms.[7]

In addition to the above, different algorithms have been tested with many comparative studies for MTSP. Some studies have compared Improved GA with Particle Swarm Optimization.[8]. One of the algorithms that are often used in TSP and MTSP problems and gives successful results is undoubtedly the GA. Jun Lie et al. presented a GA-based solution for MTSP in their work. The critical operators of the GA were analyzed using three different modes for crossover and mutation. They stated that the GA is suitable for solving MTSP, and simple city crossover and city mutation give the best performance [9]. Li et al., in another study, used the GA for Colored Travelling Salesman Problem (CTSP), a kind of MTSP. They made three different GA recommendations: GA with Greedy Initialization, Hilling Climbing GA (HCGA) and Simulated Annealing GA (SAGA). After a comprehensive analysis, it was determined that SAGA gave the best results and HCGA gave reasonable results in a short time [10]. Another algorithm used for CTSP originating from MTSP is Artificial Bee Colony Algorithm. In a large-scale study with over 2000 cities, it was seen that ABC gave more successful results than Greedy GA, Hill-Climbing GA and Simulated Annealing GA. [12]

GA was again used to minimize route distances in MTSP and to provide a balance between routes in another study. In this study where different selection and crossover combinations were compared, it was seen that both results obtained with multi-objective and mono-objective approaches were successful. It has been determined that the multi-object approach, which aims to minimize both the overall distance and the standard deviation between routes, produces more balanced solutions [13]. Lin-Kernighan Heuristic search algorithm was used for Cooperative Trajectory Planning in Multi-UCAV problem using MTSP approach [14]. The GA was also used in a study conducted with another Path Planning and Following to solve MTSP. In experimental dynamic scenarios, they observed that although the GA tends to the optimal result, it does not always provide the most optimal solution as in theory [15]. More efficient results were tried to be obtained by using the improved Partheno-GA for MTSP in another study [16].

When the literature is reviewed, it will be easily seen that the success of the GA has led to a high preference for NP-Hard and NP-Complete problems such as MTSP. Novel approaches have been developed in order to further increase the success of the algorithm. For example, in one study, the group tour construction method was used to overcome random initialization pollution [17]. Omeer et al. also made a comparison study of six different crossover operators while using GA to solve MTSP. It was concluded that Partial Matched Crossover is the best in terms of running time and Sequential Constructive Crossover is the most successful operator in determining the best solution [18].

In this study it is aimed to distribute pharmaceutical products effectively and as soon as possible. Medicine and medical equipment distribution are one of the application areas of the algorithm we have developed. This algorithm can be used in similar distribution areas. We will explain the details of effective distribution of medicines in the next section.

C. Distribution of Pharmaceutical Products

The main application area of our work is to effectively distribute medicines and medical supplies in a specified area. The pandemic process that emerged in late 2019 and affected the whole world, directed us to this issue as an implementation field. The performance of pharmaceutical and medical supplies distribution is vital in emergency situations caused by pandemic processes like Covid-19. Distributing the materials as soon as possible is not a preference but an obligation. TSP or MTSP approaches can be used for the urgent distribution of many materials that are not often used and not needed in daily life, such as surgical masks, respirators, and medical test kits. The necessity of using more than one distribution vehicle in the same region in order to realize the distribution in the shortest time has led us to use the MTSP approach. Painfully exposed to the consequences of late medical intervention or inadequate medical equipment, health ministries and non-governmental organizations around the world have sadly witnessed the importance of optimization of the deployment process.

Every healthcare institution, pharmacy or hospital that needs to be distributed represents a must-visit point. The vehicles that will make the distribution and carry the medical supplies correspond to the salesman. The number of distribution vehicles will vary according to the structure of the region where the distribution will be made and the number of distribution points.

III. PROPOSED SYSTEM

In this study it is aimed to distribute pharmaceutical products to health institutions in a specific region in the most efficient and fast way. It is accepted that there is a station or center where the materials are loaded by the vehicles in the distribution region. The necessity of visiting once by the distribution vehicles, and the condition of returning to the starting point, i.e. the distribution center after the delivery vehicles complete their duties, confront us with the MTSP. It was decided to use GA, which is one of the EA frequently used in MTSP, in order to obtain a successful solution in our scenario that turns into a classical MTSP problem. Different EA could also be used to solve the distribution of pharmaceutical products, which is a problem of NP-Hard, but we thought that GA would be more successful for the scale and conditions in our problem. In the comparative analysis studies examined in the literature review, seeing that GA is better in terms of finding optimal results and running time in problems similar to our problem has had a significant effect on our decision to choose GA.

A. Genetic Algorithm

The GA is one of the intuitive and EA inspired by the natural selection process observed in living things. GA, in which the survival of the fittest principle put forward by Charles Darwin is valid, has been built by adapting the stages of Selection, Crossover and Mutation, which are the most important elements of biological evolution, to the algorithm. This algorithm, first introduced by Holland in 1960, is mainly used in optimization and search problems. The fields of study in which the GA is used vary widely.

Each solution is named as chromosome or individual in GA terminology. Each distribution route in our problem is represented by one chromosome. While the distribution points correspond to the genes in the chromosome, the pool of these chromosomes is called the population. Child chromosomes obtained by pairing the chromosomes selected from the population represent solutions belonging to the next generation. The next generation is achieved with crossover and mutation operators in the GA, where the fittest ones are transferred to the next generation and aims to achieve the best with each generation. These processes are repeated until the best solution is found, or a specified number of iterations is reached. The flow diagram of GA is shown in detail in Figure 2. The major parameters affecting the success of the GA are Population Size, Selection Method, Crossover Method and Mutation Rate. These operators and parameters that shape the GA will be explained in detail in the following sections.

B. Objective

It is basically aimed to distribute medical materials like pharmaceutical products to all points as soon as possible. After visiting all points, the total traveling costs of the sub-routes should be calculated separately, and the cost of the longest sub route should be minimized. In this way, the time elapsed from the beginning of the distribution of the products until the distribution is completed will be minimized.

C. Chromosome

Each distribution point in this study corresponds to a gene in the chromosome structure in GA. Although the chromosome structure used for TSP and the chromosome structure used for MTSP differ, the chromosome structures used for MTSP may also differ. We decided it would be appropriate to use MTSP with one depot for our scenario.

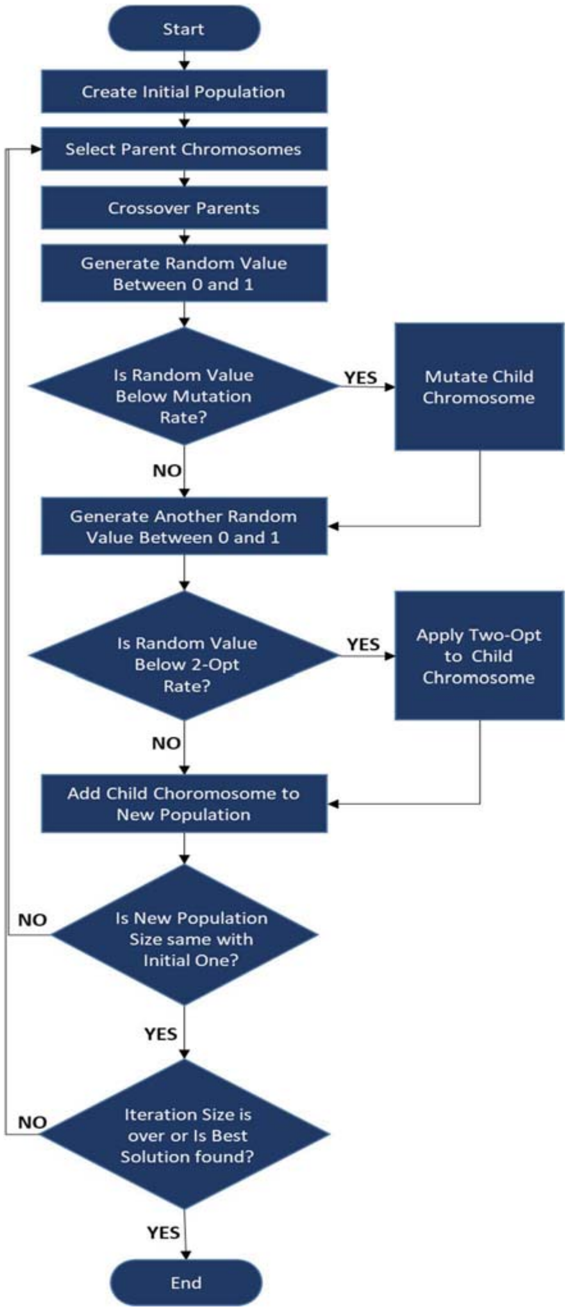

Figure 2. Flow Chart of Proposed Algorithm

Where n is the number of distribution points and m is the number of salesmen; the example chromosome structure we have created for $n = 10$ and $m = 3$ is shown in Figure 3.

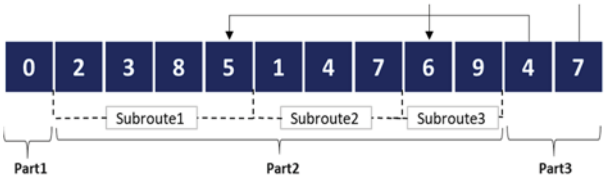

Figure 3. Chromosome Structure.

Point 0 is the starting point for all salesmen and represents one depot. The last two numbers (salesman number - 1) indicate the index of the final point of sub-routes. For this chromosome; sub route 1 = 0 – 2 – 3 – 8 – 5 – 0, sub route 2 = 0 – 1 – 4 – 7 – 0 and sub route 3 = 0 – 6 – 9 – 0. First gene of the chromosome which is Part 1 represents the start and the end point, as shown in the example. Part 2 represents the numbers of the points, while Part 3 indicates the index of the end point of the sub routes.

D. Fitness Function

The fitness function takes the chromosome as a parameter and produces the fitness value of that chromosome. New generation chromosomes, in other words, solutions, are created by using the chromosomes in the current generation. While the next generation is being created, the selection of the parent chromosome is based on this fitness value because it is desired that the solutions that are the fittest are transferred to the next generations for optimization. Therefore, well defined Fitness Function plays a very important role in the success of GA. Our vital criterion which determines the success of the solution is the cost of the longest sub route. Fitness value should be higher when the cost of the longest sub route of the chromosome becomes lower. As a result, the fitness function equals to 1/cost of the longest sub route.

E. Initial Phase

The initial population is the beginning of the evolutionary development process. There are two essential criteria for the initial population: Initial population creation method and initial population size. The initial population size taken as a parameter at the beginning of the program keeps the same value throughout the program. As for the initialization method, two types of methods are generally used: the heuristic method and the random method. Although both methods are successful, the random method is better in terms of providing diversity and leading to global optimum. Therefore, we chose the random start method. Chromosomes were created by randomly assigning all genes in accordance with the structure described in the chromosome section in this phase. The creation of the chromosome process is repeated until the chromosome number reaches initial population size parameter.

F. Selection

The process of selecting the parent chromosomes is vital for the creation of the next generation and for producing optimal results. There are several methods for the selection phase: Tournament Selection, Roulette Wheel Selection, Stochastic Universal Sampling, Linear Rank Selection, Exponential Rank Selection and Truncation Selection. These methods are basically divided into two categories as Elitist and Proportional. Furthermore, it is very important to be able to maintain diversity in order not to be stuck at the local optimum. Accordingly, we choose the Tournament Selection. The tournament size is set as 4. Hence, four random chromosomes were selected and competed in a tournament. Winner chromosome is assigned as Parent 1. Parent 2 is selected in the same way. Parent 1 and Parent 2 will be used for creation of child chromosome.

G. Crossover

The crossover is an operator inspired by the crossing over of DNAs in biology. The solution quality and computation time of the algorithm can vary depending on the crossover method. There are several crossover types in GA: Single Point Crossover, N Point Crossover, Uniform Crossover, Three Parent Crossover, Arithmetic Crossover, Partially Mapped Crossover, Order Crossover and Cycle Crossover. In another comparative study, four different crossover types were compared, and it was stated that the single point crossover gave the best result. Our crossover method steps are detailed below, and the process is shown in Figure 4.

Determine random value as r/ Find point r and next in both chromosomes/ Calculate the cost between r and next for two chromosomes/ Add pair which cost is less than other chromosome's to Child Chromosome/ Assign next point from r as new r/ Repeat steps 2, 3, 4 and 5 until the child chromosome is complete.

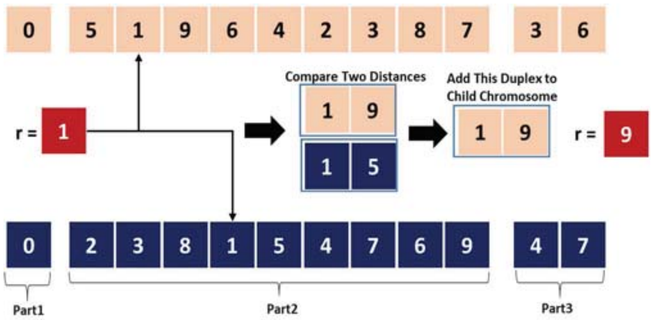

Figure 4. Crossover Process

H. Mutation

One of the most important characteristics of EA is maintaining genetic diversity and not getting stuck at local optimum points. There are also different types of this operator inspired by the mutation process in biology. In order that the GA is not a primitive search algorithm, the mutation process should not be applied to all chromosomes. While the mutation process provides gene diversity by applying it with a probability, its application with a significant probability also ensures that successful solutions from previous generations are passed on to the next generations. The mutation rate should not be high because the high mutate rate can prevent the population from converging to a particular optimal solution. In other words, while the Crossover operator brings the solution closer to the best, the mutation operator expands the search space for the best solution. Also, there is no standard mutation rate for all kind of problems. Mutate rate varies based on infrastructures of problem and algorithm. We tried different mutate rates for our algorithm and decided to use "0.01" in our experiments.

I. Termination

Algorithm termination is commonly attributed to two conditions. The first is that the algorithm reaches the best value. The second is the condition of reaching the predetermined number of iterations. We took the iteration number as a parameter for our program and made computation time calculations for different values. At the same time, we used the 2-Opt Algorithm (2-Opt) in order to reach the most optimal values in earlier iterations and to strengthen our algorithm.

J. Two-Opt Algorithm

The algorithm as seen in Figure 3, we made use of the 2-Opt within a certain probability. The 2-Opt is a simple local search algorithm that can be used in the TSP. It obtains a new route by crossing. It compares the current route with the new one and assigns the better one as the new one. Complete 2-Opt has the disadvantage of increasing computation time while evaluating all possible options. That's why we used the 2-Opt according to a certain probability. We measured the success of the algorithm and the computational time by using different values for the 2-Opt rate. In addition to all, we implemented the 2-Opt on sub-routes separately.

IV. EXPERIMENTAL RESULTS

Our developed algorithm was executed on a machine which is detailed as in Table 1. All test process is carried out by this machine. Computation time calculations are valid for this PC.

Table 1. Test Machine Features

Computer	Lenovo – HuronRiver Platform
Operating System	Microsoft Windows 10 Pro
CPU	Intel® Core™ i5-2410M CPU @ 2.30GHz, 2301 Mhz, 2 Cores, 4 Logical
RAM	4,00 GB
IDE	PyCharm 2020.1 (CE)

Determining the parameters is very crucial for the success of GA-based algorithms. Our parameters and their values are shown in Table 2.

Table 2. Proposal GA Parameters

Parameter	**Value**
Selection Method	Tournament
Crossover Method	HGA Crossover
Mutation Method	One Point Swap Mutation
Population Size	100
Mutate Rate (%)	1
2-Opt Rate (%)	1
Elitism Rate (%)	2
Iteration Size	50, 100, 1000

When we run our proposal algorithm using the parameters as shown in Table 2, the following graph, which is in accordance with GA concept, is obtained as shown in Figure 5. As the generation proceeds, solution costs diminish. After a certain number of iterations, the decrease in solution cost is very small.

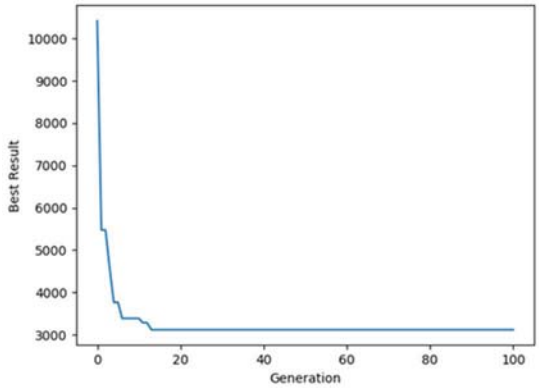

Figure 5. Solution Costs Based On Generation

It is aimed to distribute pharmaceutical products to distribution points as soon as possible. It is assumed that the vehicles have a speed of 30 km/h. Distance should be minimized in order to decrease distribution time based on the formula "Time = Distance / Velocity". Distribution times for cases from m = 1 to m = 5 were calculated using "bayg29", "att48", "berlin52", "bier127" and "ali535" datasets. These datasets were taken from TSPLIB, and they contain coordinate information for a different amount of points. The distribution time value of the case of m=1 was assumed to be 1 in order to normalize the results of other m values. The comparative chart created for different m values and data set is shown in Figure 6. As can be seen in the graph, distribution time decreases depending on the increase in the number of salesmen and the decrease after m=1 was quite remarkable.

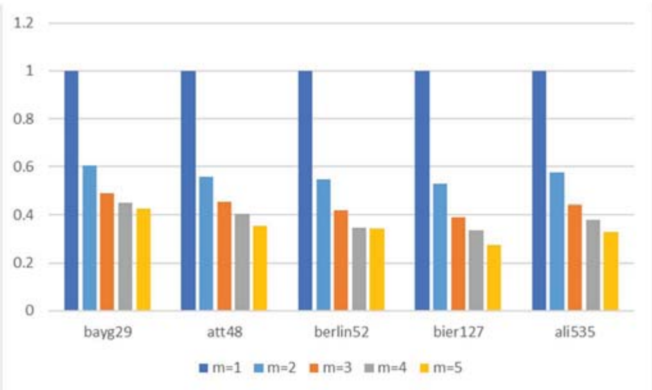

Figure 6. Distribution Time of Different Datasets Based on Salesman Number

After experimental results, it was observed that our proposed algorithm supported by 2-Opt gave successful results. Point 0 represents one depot of paths using the "byg29" dataset. The chromosome sequence of a successful solution after acceptable iteration = [0, 1, 28, 2, 25, 4, 8, 11, 5, 20, 9, 19, 3, 14, 17, 16, 21, 13, 10, 18, 23, 12, 27, 7, 26, 22, 6, 24, 15, 9, 19]. The path plot of this chromosome is shown in Figure 7.

While producing solutions for real-life problems, the time required to reach a successful solution, namely the computation time of the program, is also an important factor in addition to the solution quality. In this context, we calculated the computation time of our program with different parameter value as indicated in Table 3.

As computation time values were at an acceptable level, it was observed that the effect of 2-Opt on computation time decreases especially with the decrease of n, population size, and iteration size parameters.

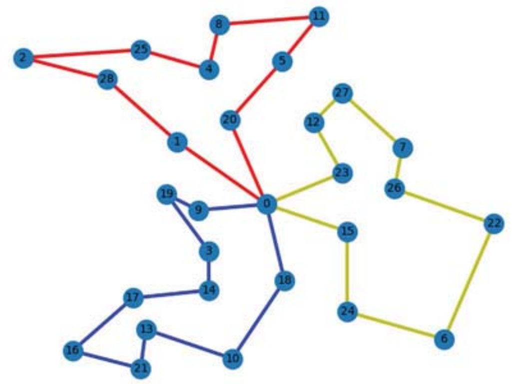

Figure 7. Paths of Distribution Vehicles When m=3

		2-Opt Rate		***0***	***0.05***	***0.1***	***0.2***	***0.3***
iter_size	***pop_size***	***m***	***n***	***Computation Time(sec)***				
50	50	3	52	0.79	0.812	0.98	1.128	1.25
100	100	3	52	2.9865	3.4108	3.809	4.8925	5.71
100	100	3	29	1.8648	1.9068	2.1976	2.3695	2.6973
100	100	2	29	1.8628	2.0457	2.1836	2.3897	2.7523
100	50	3	29	0.96	0.97	1.093333	1.23	1.336667
100	50	2	29	0.98	1.153333	1.1	1.32	1.393333
50	***50***	***3***	***29***	***0.48***	***0.53***	***0.54***	***0.57***	***0.62***

Table 3. Computation Times Based On 2-Opt Rate and Parameters

V. Conclusion

Thanks to developments in computer science, efficient solutions can be produced for many fields and various real-life problems can be overcome. One of the today's problems is the efficient distribution of critical materials such as pharmaceutical products. This problem, which increases its importance especially in global crisis environments like Covid-19 pandemic, is considered as a kind of MTSP. GA, which is one of the powerful EA, was used to solve the MTSP. Our proposal algorithm was also strengthened with 2-Opt and produced quite successful solutions for different salesman numbers. It was observed that the distribution time with MTSP approach is significantly shorter than the one with TSP. In addition to the success quality of the solutions, computation time calculations were made for different parameters, and it was measured that the times were at a reasonable level. This study, which provides the efficient distribution of pharmaceutical products with our proposal algorithm, will be expanded with the development of a new concept for the mutation phase, which is a crucial operator of GA as future works.

Depending on the number of constraints, the complexity of the problem will be increased, therefore in the ongoing works the use of parallel programming techniques, such as parallel genetic algorithms[19], can be used to increase the efficiency of the system.

References

[1] P.R. de Oliveria da Costa, S. Mauceri, P. Carroll and F. Pallonetto, "A Genetic Algorithm for a Green Vehicle Routing Problem," Electronic Notes in Discrete Mathematics, vol. 64, pp. 65–74, February 2018.

[2] U. Cekmez, M. Ozsiginan, and O. K. Sahingoz, "Multi-UAV Path Planning with Parallel Genetic Algorithms on CUDA Architecture", In Proceedings of the 2016 on Genetic and Evolutionary Computation Conference Companion (GECCO '16 Companion), Association for Computing Machinery, New York, NY, USA, 2016, pp. 1079–1086.

[3] E. N. Kencana, I. Harini and K. Mayuliana, "The Performance of Ant System in Solving Multi Traveling Salesman Problem," Procedia Computer Science, vol. 124, pp. 46–52, 2017.

[4] P. Junjie and D. Wang, "An Ant Colony Optimization Algorithm for Multiple Travelling Salesman Problem," First International Conference on Innovative Computing, Informatin and Control(ICICIC 2006), 30 August – 1 September 2006, Beijing, China.

[5] P. Kitjacharoenchai, M. Ventresca, M. Moshref-Javadi, S. Lee, J. M. A. Tanchoco and P. A. Brunese, "Multiple traveling salesman problem with drones: Mathmetical model and heuristic approach," Computers & Industrial Engineering, vol. 129, pp. 14–30, March 2019.

[6] A. E. Carter and C. T. Ragsdale, "A new approach to solving the multiple traveling salesperson problem using genetic algorithms," European Journal of Operational Research, vol. 175, pp. 246–257, November 2006.

[7] C. Jiang, Z. Wan and Z. Peng, "A new efficient hybrid algorithm for large scale multiple traveling salesman problems," Expert Systems with Applications, vol. 139, 112867, January 2020.

[8] H. Zhou, M.Song and W. Pedrycz, "A comparative study of improved GA and PSO in solving multiple traveling salesman problem," Applied Soft Computing, vol. 64, pp. 564–580, March 2018.

[9] J. Li, Q. Sun, M. Zhou and X. Dai, "A New Multiple Traveling Salesman Problem and Its Genetic Algorithm-Based Solution," 2013 IEEE International Conference on Sytems, Man and Cybernetics, 13-16 October 2013, Manchester, UK.

[10] J. Li, Q. Sun, M. Zhou, Z. Yu and Z. Dai, "Colored Traveling Salesman Problem and Solution," IFAC Proceedings Columes, vol. 47, pp. 9575-9580, 2014.

[11] T. Turker, O. K. Sahingoz and G. Yilmaz, "GPU-Accelerated Flight Route Planning for Multi-UAV Systems Using Simulated Annealing", International Conference on Artificial Intelligence: Methodology, Systems, and Applications AIMSA, 2016, pp. 279-288.

[12] X. Dong, Q. Lin, M. Xu and Y. Cai, "Artificial bee colony algorithm with generatingneighbourhood solution for large scalecoloured traveling salesman problem," IET Intelligent Transport Systems, vol. 13, no. 10, pp. 1483–1491, 2019.

[13] R. M. F. Alves and C. R. Lopes, "Using Genetic Algorithms to minimize the distance and balance the routes for themultiple Traveling Salesman Problem," 2015 IEEE Congress on Evolutionary Computation (CEC), 25 – 28 May 2015, Sendai, Japan.

[14] X. Gui, X. Cao, Y. Xie, J. Chen and X. Sun, "Cooperative Trajectory Planning for Multi-UCAV using MultipleTraveling Salesman Problem," 2016 35th Chinese Control Conference (CCC), 27- 29 July 2016, Chengdu, China.

[15] O. N. A. Sanchez and R. F. De la Rosa, "Path Planning and Following using Genetic Algorithms to Solve the Multi-Travel Salesman Problem

in Dynamic Scenarios," 2017 18th International Conference on Advanced Robotics (ICAR), 10 – 12 July 2017, Hong Kong, China.

[16] Z. Wang, X. Fang, H. Li and H. Jin, "An Improved Partheno-Genetic Algorithm With Reproduction Mechanism for the Multiple Traveling Salesperson Problem," IEEE Access, vol. 8, pp. 1102607–102615, 2020.

[17] D. R. Singh, M. K. Singh and T. Singh, "Multiple Traveling Salesman Problem using novel Crossover and Group Theory," International Conference on Computing, Communication and Automation (ICCCA2017), 5 – 6 May 2017, Greater Nodia, India.

[18] M. A. Al-Omeer and Z. H. Ahmed, "Comparative study of crossover operators for the MTSP," 2019 International Conference on Computer and Information Sciences (ICCIS), 3 – 4 April 2019, Sakaka, Saudia Arabia.

[19] U. Cekmez, M. Ozsiginan, M. Aydin, O.K. Sahingoz, UAV Path Planning with Parallel Genetic Algorithms on CUDA Architecture, WCE, IAENG, Lecture Notes in Engineering and Computer Science, 1, 2014, pp. 551-557.