

Solving Dynamic Vehicle Routing Problem using Enhanced Genetic Algorithm with Penalty Factors

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Abstract

The vehicle routing problem (VRP) has become one of the focus issues in operations research and management sciences over the past two decades. One of its principal branches is the dynamic vehicle routing problem (DVRP), which can receive new order requests during the service process and make a timely response, unlike static vehicle routing problems (SVRP) where all information is known before the optimization starts. In this paper, we solve DVRP while using an enhanced genetic algorithm (GA) that tries to increase both diversity and global searching ability. The maximum saving method and the nearest neighbor method are adopted in the crossover operation to improve the path selection. Considering the near distance priority service principle (NDPSP) in the actual operation, a new assessment scheme with penalty factors is applied to our individual assessment. In addition, a paired-t test as a non-parametric statistical analysis is implemented to demonstrate the efficiency of the enhanced genetic optimization algorithm, based on a publicly available VRP benchmark, which includes 21 data sets. Analysis results show that our approach outperformed the published approaches based on optimizing results.

Keywords: dynamic vehicle routing problem; dynamic optimization; genetic algorithm; near distance priority service principle; p-value

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1. Introduction

As we all know, life has been significantly improved in the past few decades due to the progress of transportation and logistics [19]. Meanwhile, urbanization rate keeps growing and the urban population rate will consistently grow as well. As a result, research on the routing problem, especially the vehicle routing problem (VRP), which can effectively reduce vehicle driving distance and reduce transportation costs, has increased greatly during the last few decades.

VRP defines a class of combinatorial optimization problems to optimize vehicle travel during round trips. Previous researches have demonstrated how vehicle routing optimization can lead to significant economic savings [3]. The earliest VRP was proposed by Dantzig et al [7] in 1959, which was the traveling salesman problems (TSPs). Now, it has produced many different extension patterns, such as multiple depots VRP [15,25], periodic VRP [23], and pickup and delivery VRP [18,24].

We investigate that most studies are about static VRP (SVRP) [6,14], which is where all data is known before the optimization has started, and the data is no longer changed during the service. However, in practice, new information is received and processed over time, and new information can be obtained in real time due to advances in communication and information technologies. Considering these facts, a new variant of VRP classified as DVRP [1,4,11,13,17] has inspired many scholars.

There are two major contributions in this paper. The first contribution is solving DVRP by using an enhanced genetic optimization algorithm that tries to increase both diversity and global searching ability. To enhance GA, three modifications

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are proposed: the selection process consists of a tournament select and elitist strategy to improve the global searching ability, two different crossover methods are adopted to increase diversity, and the penalty factor is employed while considering the near distance priority service principle when evaluating individual fitness.

The second contribution is that a paired-t test is applied to evaluate the effect of the enhanced GA with penalty factors on solving DVRP. In statistical hypothesis testing, the p-value or probability value is the probability for a given statistical model that, the statistical summary (such as the sample mean difference between two compared groups) would be the same as or greater magnitude than the actual observed results when the null hypothesis is true. In many kinds of literature, we found that few scholars have used a paired-t test to demonstrate the efficiency of the proposed algorithm. Therefore, a paired-t test is adopted to assess the validity of enhanced GA and the effectiveness of the penalty factors.

The structure of this paper is organized as follows. In section 2, a general description of DVRP dynamic scheduling manager is introduced. In section 3 we discuss our experimental methodology and experimental findings are discussed in section 4. Finally, we conclude by discussing the implications of our results and offer suggestions for the future work in section 5.

2. Dynamic vehicle routing problem

The dynamic vehicle routing problem (DVRP) is developed from the static vehicle routing problem (SVRP). The SVRP is an optimization problem that gets the best solution with all data having been known in advance and without changes. The difference between DVRP and SVRP is that optimization problems are constantly changing, perhaps new orders appear, previous orders are withdrawn, and so on. This section will introduce the definition of DVRP we studied, and the dynamic scheduling manager for solving DVRP will be given.

2.1. A general description

The SVRP can be modeled in mathematical terms. $G = (V, A)$ is a weighted complete digraph, where direction indicates service order and weight is the distance between nodes. In addition, $V = \{0, 1, \dots, n\}$ is a set of all nodes including the depot (0), and all customers (1, ..., n). $A = \{(i, j) | i, j \in V\}$ are a set of arcs. Each one is related to driving time t_{ij} . q_i represents the demand of the customer i . Label Q_1, \dots, Q_n represents the maximum capacity of vehicles 1, ..., n.

In DVRP, the main difference is that new orders can be received after the jobs have started. Therefore, the DVRP can be described as followed: all received customers must be served from a depot. There are v vehicles to provide services for all customers, and each vehicle has a maximum capacity limit and cannot exceed the limit during service. Each customer can only request a vehicle to achieve the demand. New orders can be received during the service.

A graph can be adopted to represent a simple example of DVRP. As shown in Figure 1, the thick solid lines indicate the customers that have been served. The solid lines indicate that the service route has not been arranged. The dotted lines indicate the route to be rearranged when a new customer request is added. Other explanations are marked in Figure 1.

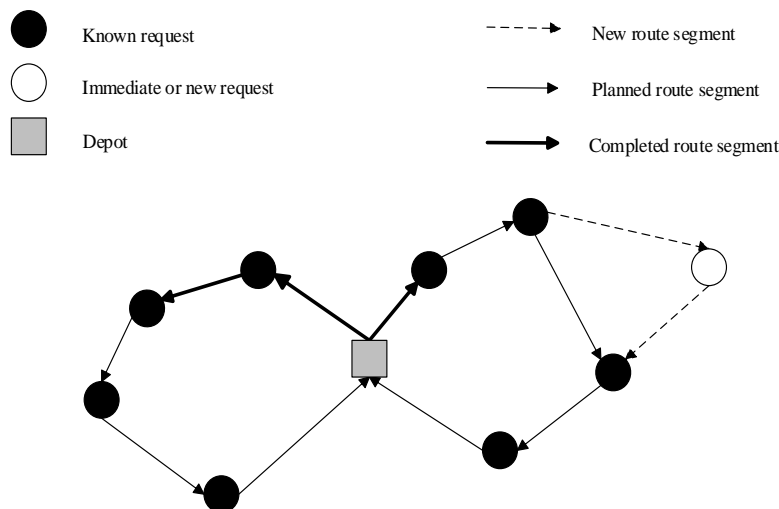


Figure 1. An example of a DVRP with two vehicles, 8 known customers and a new customer

2.2. Dynamic scheduling manager

In this paper, we investigate the DVRP model put forward by Montemanni [16], which extended DVRP as the standard VRP and decomposed DVRP into a series of static VRP. We use the same model that divides a working day into periods of equal duration. The customer who can be processed by the next time slice is submitted to the driver for processing, and the remaining unprocessed customers are presented to the optimizer as a static instance with subsequent orders until all the customers are processed. The event manager and the enhanced genetic optimization algorithm are shown in Figure 2.

Our approach is based on the idea of dividing the working day into time slices, so there are some key time parameters that should be considered while solving DVRP.

- The working day: T determines the total length of working time that is available to serve the customers each day. In the experiment, the length of a workday is set to 1500.
- The cut-off time: T_{co} is the deadline for receiving the new orders. The customer requests received before the deadline T_{co} will be processed on a working day, and requests received after T_{co} will be processed on the following day. T_{co} is generally set to half the time of the working day, that is, $0.5 \cdot T$.
- The advanced commitment time: T_{ac} is used because a driver needs a response time before leaving from the last location to the next one, so the orders must be committed to the driver T_{ac} seconds in advance.

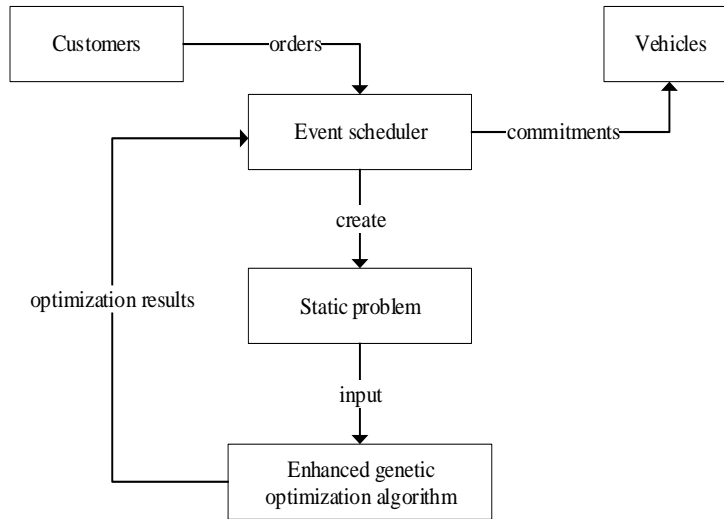


Figure 2. The event manager and enhanced genetic optimization algorithm

After each time slice, the optimization results of the current time slice can be obtained, and then the customers that start within the next $\frac{T}{n_{ts}} + T_{ac}$ are submitted to the driver, where n_{ts} represents the number of time slices. Furthermore, it should be noted that the time window of each data set is not the same. We should map the time window of each data set to 1500, while the available time and the duration time should also be adjusted accordingly.

3. Enhanced genetic optimization algorithm

Genetic Algorithm (GA) is an evolutionary technique that uses operators such as mutation and crossover, and then selects the most fitted element as a solution for problems optimization [21]. A large number of vehicle routing optimization strategies based on Genetic Algorithms (GA) have been proposed, but it still has a lot of room for improvement [28]. In this section, we introduce the enhanced GA for DVRP.

3.1. Tournament selection and elitist strategy

The selection operation determines how individuals can be selected to reproduce (crossover and mutation), which determines the direction of overall genetic evolution. In this article, the selection part has two stages. The first stage is the tournament selection [26]. In this paper, we will build a new tournament set each time we decide to choose an individual,

which aims to ensure the diversity of individuals. In addition, we modified the standard tournament selection to make it possible for individuals with poor fitness to have a higher chance of being selected. The modified version is shown in Figure 3, where r is a random value and ρ is the selection pressure.

A tournament selection cannot guarantee that individuals with the best fitness will be chosen. To make sure the best individuals are able to reproduce, the elitist strategy is considered. Yanlian Wu et. al [27] have proven that the amount and diversity of elite individuals are increased with the regeneration of the elite subpopulation. In our approach, 4% of the worst solutions are replaced by 4% of the best solutions in the last generation. The optimal solution may be destroyed, but it can speed up the global search optimization and avoid local optimization as much as possible. The complete selection process diagram is shown in Figure 3. It is important to note that we will reserve the best individual in the elite population without crossover and mutation.

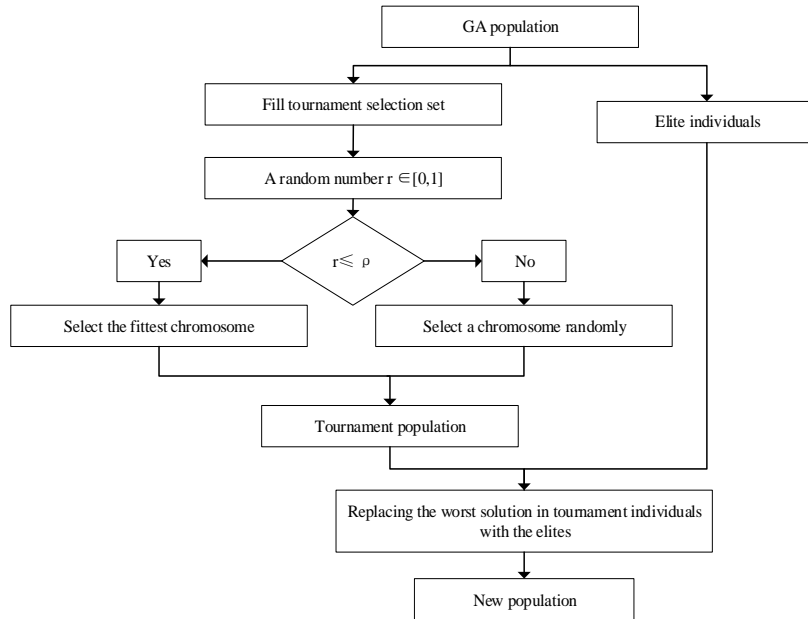


Figure 3. The combination of modified tournament selection and elitist strategy

3.2. Crossover

The crossover process is the main way for the population to produce new individuals. However, traditional crossover operators, like Partially-Mapped-Crossover (PMX) [8], are not suitable for solving DVRP, which requires high efficiency of the algorithm. Considering DVRP's nature, we made some improvements on the genetic crossover.

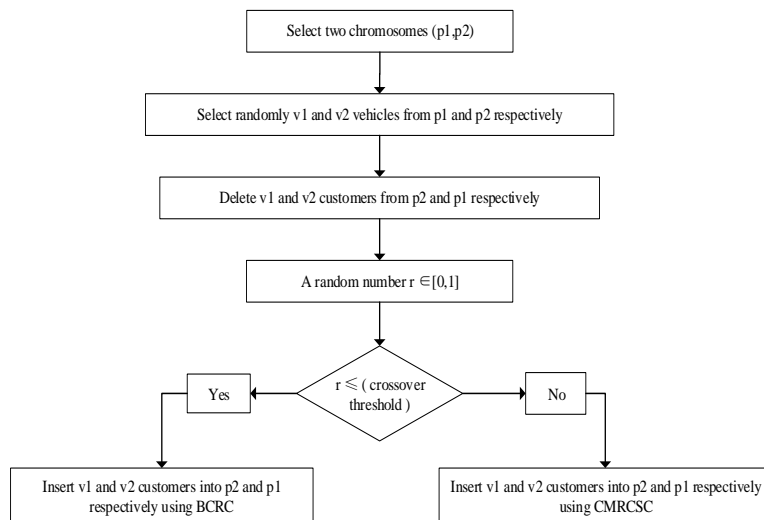


Figure 4. The new crossover operation

In our approach, we adopted two crossover strategies. The first is that the Best-Cost Route Crossover (BCRC) employed in [12,20]. The second is the closest distance and maximum saving route crossover with priority to satisfy the capacity constraint (CMRCSC). It will successively determine whether the remaining capacity of assigned vehicles can meet the customer requirement when a customer will be inserted. If no vehicle meets the requirement, we will assign an empty vehicle to serve. Once a vehicle is selected, the customer that has been assigned to the vehicle but has not been served will be considered if it is the closest one to the inserted customers. Then, a customer is inserted before or after the selected customer according to the maximum saving method. The step is like a normal BCRC, which has been described in [10]. There is just a difference in the way you insert customers. The modified version is shown in Figure 4.

3.3. Mutation

Mutation is an important genetic operation that helps to maintain the genetic diversity of the population to achieve a good solution to an optimization problem [2]. The mutation we adopt is reversed, that is, to randomly select a gene segment in the chromosome and then reverse it to form a new individual. The schematic diagram is shown in Figure 5.

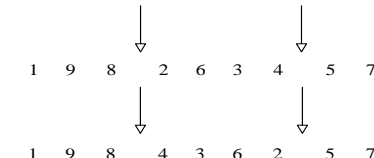


Figure 5. An example of inversion mutation

3.4. Fitness evaluation method

The choice of fitness function can be a difficult and important step in Genetic Algorithms (GA). In many previous studies, an individual was evaluated based on direct distance calculation. Considering the near distance priority service principle (NDPSP) and the driving distance, we add a penalty factor that violates the NDPSP when calculating individuals' fitness. The design of the penalty factor is described as follows.

Let L_{ij} represent the direct distance between the customer i and j , and L_{i*} represents the distance set from customer i to other customers. If customer j is the next one to be visited after visiting customer i , the penalty factor between i and j is shown as Equation (1).

$$p_{ij} = \frac{L_{ij} - \min(L_{i*})}{\max(L_{i*})} \quad (1)$$

Now we use L'_{ij} to represent the distance between i and j after integrating the penalty factor parameter. Then, L'_{ij} can be obtained through Equation (2).

$$L'_{ij} = L_{ij} \times (1 + p_{ij}) \quad (2)$$

An individual x is assigned a fitness value $F_{DVRP}(x)$ according to Equation (3).

$$F_{DVRP}(x) = \sum_{i=1}^m \text{Cost}(L'_i) \quad (3)$$

where L'_i is the length of the i^{th} route after adding the penalty factor.

4. Experimental results and discussion

This section is devoted to the experimental evaluation of enhanced GA for solving DVRP based on public VRP benchmark datasets, which consist of three separate VRP sources, namely Taillard [22] (12 instances), Christophides and Beasley [5] (7 instances) and Fisher et al. [9] (2 instances).

The experiments have been coded in MATLAB 2016a, on a 3.20GHz/8GB Intel(R) Core(TM) i5-6500 machine. The genetic parameters used in the experiment are shown in Table 1. For the DVRP model, n_{ts} is set to 25, T_{ac} to 0.01 of the working day, and T_{co} to 0.5 of a working day. A working day is set to 1500. The execution time of the optimization program in each time slice is 30 seconds.

Table 1. Genetic parameter setting

Parameters	Value
Population number	200
Selection probability	0.8
Cross probability	0.9
Mutation probability	0.1
Processing time	30
Retained number	1
Elite ratio	4%

From Hanster's introduction, we know that the three data sets are randomly distributed according to different distribution criteria. Table 2 shows the distribution characteristics of the three data sets. Then, we separately extract a data set from three data instances to analyze the experimental results. The following Table 2 describes the distribution characteristics of the three data sets, which have been introduced in [10].

Table 2. Topology details of the various service areas

Type	Customers	Distribution
f	71-134	Most customers are concentrated in a central area where customers are further reduced from the center
tai	75-150	Mixed uniform and clustered
c	50-199	Uniform and cluster

The following Figure 6 shows the roadmap for the three sets of data sets c100, tai100b, and f134 in obtaining the optimal solution.

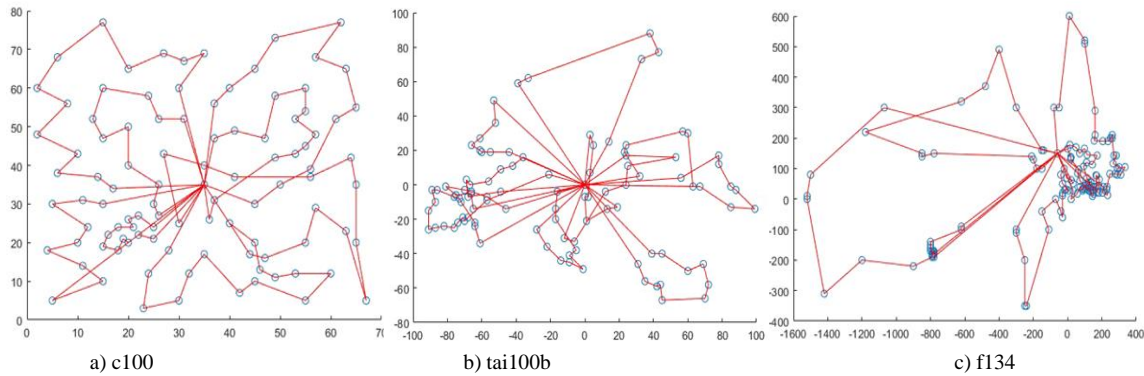


Figure 6. Roadmap for instance c100, tai100b and f134 respectively

4.1. Discussion of different fitness evaluation strategy

In this section, we discuss how to combine short-distance priority services while evaluating the individual fitness. The first evaluation criterion is to minimize the penalty distance (MPD) considering the near distance priority service principle (NDPSP). The second is to minimize the driving distance (MDD) without considering the NDPSP. Considering the NDPSP and the driving distance, minimize the total distance (MTD), which consists of penalty distance and driving distance as the third evaluation criterion.

It can be seen from Table 3 that if NDPSP and driving distance are considered, better experimental results can be obtained. The best result appears if only NDPSP is observed without considering the driving distance. Considering both the best solutions and average solution, it is more conducive to our experiment to solve DVRP if the penalty factor is set to $1 + p_{ij}$ to minimize the total distance.

Table 3. The comparison of different strategy

problem	MPD		MDD		MTD	
	Best	Average	Best	average	Best	average
c50	581.83	600.152	562.913	598.677	556.287	588.166
c75	959.157	996.286	930.14	977.290	928.967	972.255
c100	938.523	1017.164	975.862	1030.876	933.59	969.273
c100b	922.237	1002.298	878.44	969.170	877.490	900.347
c120	1170.171	1296.449	1101.034	1244.05	1077.418	1229.802
c150	1256.425	1289.317	1188.667	1262.78	1187.381	1254.064
c199	1650.299	1670.043	1538.928	1605.718	1535.723	1624.338
tai75a	1756.194	1929.27	1786.631	1970.881	1730.478	1808.826
tai75b	1504.4	1570.361	1404.242	1593.689	1402.657	1528.083
tai75c	1445.24	15616.11	1438.929	1511.614	1431.108	1478.713
tai75d	1480.222	1610.966	1420.516	1575.941	1408.469	1446.93
tai100a	2312.442	2442.534	2219.652	2385.417	2195.675	2257.188
tai100b	2300.397	2420.655	2209.544	2398.391	2095.018	2291.337
tai100c	1615.87	1737.427	1499.261	1620.61	1484.119	1573.402
tai100d	1832.596	1975.273	1743.094	1850.463	1733.916	1841.071
tai150a	3741.882	3950.674	3579.353	3744.659	3485.285	3737.567
tai150b	3025.217	3426.433	3115.117	3299.417	3075.221	3202.524
tai150c	2798.45	2971.733	2664.965	2818.415	2649.463	2709.919
tai150d	3145.787	3343.525	2896.388	3089.554	2866.388	2997.459
f71	291.98	305.509	277.367	301.418	276.607	289.495
f134	12762.42	13304.3	12207.25	12720.91	12073.55	13266.72
total	34437.34	50866.67	45638.3	48569.94	45004.81	47967.48
average	1812.492	2677.193	2173.252	2312.854	2143.086	2284.166

Meanwhile, a paired-t test is applied to perform statistical analysis, which can investigate whether there are statically significant differences between different strategies according to quality or not. Suppose that the goal of MTD would give solutions with lower route lengths than other strategies. A one-sided alternative hypothesis, H_1 , is given as Equation (4):

$$H_1 : \mu_{MTD} - \mu_{OA} < 0 \quad (4)$$

where μ_{OA} refers to the other approach used in a statistical comparison. Table 4 shows pairs, mean differences for MPD, MDD, MTD, and p-value at a significance level of $\alpha=0.05$. As seen from the Table 4, MTD is statistically significantly different from MDD and MPD. This analysis indicates that MTD strategy is more appropriate for our approach.

Table 4. Paired-t test based on the published systems

MTD VS	Mean Difference	the
MDD	-30.166	0.968
MPD	-118.425	0.878

4.2. Comparison of different experimental methods

Table 5 shows the comparison among all systems, where the bold entries indicate the best-found solutions in this paper. GA-DVRP with penalty factor found 16 out of 21 new best solutions, compared to the proposed GA-based DVRP, which found 5 out of 21 new best solutions, and no new solutions were found using the Ant System. When comparing the average solutions, GA-DVRP with penalty factor gets better averages in 18 out of 21 problems compared to the proposed GA-based DVRP, which gets the better best solution in 12 out of 21 problems compared to DVRP-GA. No better solutions are found in the Ant System.

Table 6 shows how much each method enhances and differs from the ant colony system, e.g., DVRP-GA improves the ant colony system by 3.20% and 5.02% for the best and average results respectively. This suggests that the enhanced GA drives more exploitation, while GA-DVRP with penalty factor is more effective in solving DVRP.

From Table 5 and Table 6, considering both the best solutions and average solutions, we conclude that GA-DVRP with penalty factor outperforms other existing approaches based on the comparison of experimental results.

Table 5. Solution comparison with other systems

problem	Ant System		DVRP-GA		Proposed GA-based DVRP		enhanced GA DVRP with penalty factors	
	Best	Average	Best	Average	Best	Average	Best	Average
c50	631.3	681.86	570.89	593.42	566.01	597.34	556.2874	588.1656
c75	1009.36	1042.39	981.57	1013.45	944.46	990.78	928.9668	972.2551
c100	973.26	1066.16	961.1	987.59	943.89	988.15	933.59	969.2726
c100b	944.23	1023.6	881.92	900.94	869.41	904.03	877.4903	900.3474
c120	1416.45	1525.15	1303.59	1390.58	1288.66	1399.4	1077.418	1229.802
c150	1345.73	1455.5	1348.88	1386.93	1273.5	1359.25	1187.381	1254.064
c199	1771.04	1844.82	1654.51	1758.51	1646.36	1700.54	1535.723	1624.338
tai75a	1843.08	1945.2	1782.91	1856.66	1744.78	1823.71	1730.478	1808.826
tai75b	1535.43	1704.06	1464.56	1527.77	1441.35	1546.18	1402.657	1528.083
tai75c	1574.98	1653.58	1440.54	1501.91	1433.73	1502.56	1431.108	1478.713
tai75d	1472.35	1529	1399.83	1422.27	1408.48	1434.56	1408.469	1446.93
tai100a	2375.92	2428.38	2232.71	2295.61	2181.31	2290.95	2195.675	2257.188
tai100b	2283.97	2347.9	2147.7	2215.39	2119.03	2212.58	2095.018	2291.337
tai100c	1562.3	1655.91	1541.28	1622.66	1504.63	1589.76	1484.119	1573.402
tai100d	2008.13	2060.72	1834.6	1912.43	1793.64	1916.03	1733.916	1841.071
tai150a	3644.78	3840.18	3328.85	3501.83	3280.79	3449.32	3485.285	3737.567
tai150b	3166.88	3327.47	2933.4	3115.39	2885.94	3073.58	3075.221	3202.524
tai150c	2811.48	3016.14	2612.68	2743.55	2593.78	2759.96	2649.463	2709.919
tai150d	3058.87	3203.75	2950.61	3045.16	2911.47	3010.34	2866.388	2997.459
f71	311.18	358.69	301.79	309.64	288.3	309.49	276.607	289.4946
f134	15135.51	16083.56	15528.81	15986.84	14871.4	15789.8	12073.55	13266.72
total	50876.23	53794.02	49202.73	51088.53	47990.92	50648.31	45004.81	47967.48
average	2422.678	2561.62	2342.987	2432.787	2285.282	2411.824	2143.086	2284.166

Table 6. The summary of each system

Methods	Ant System		DVRP-GA		Proposed GA-based DVRP		Enhanced GA with penalty factor DVRP	
Criteria	Best	Average	Best	Average	Best	Average	Best	Average
Count	0	0	1	4	7	5	16	18
Worse by (%)	-	-	3.20%	5.02%	5.60%	5.80%	11.54%	10.83%

We use a paired-t test as introduced in section 4.1 to analyze the significant differences between enhanced GA with penalty factors and other heuristic approached according to quality. Table 7 shows pairs, mean differences for Ant System, DVRP-GA, Proposed GA-based DVRP and p-values at a significance level of $\alpha=0.05$. This analysis indicates that the enhanced GA with penalty factors is the most effective heuristics recently proposed in literature.

Table 7. A paired-t between different approaches

Enhanced GA with penalty factors VS	Mean Difference	p-value
Ant System	-279.591	0.743
GA-DVRP	-199.901	0.818
Proposed GA-based	-142.196	0.866

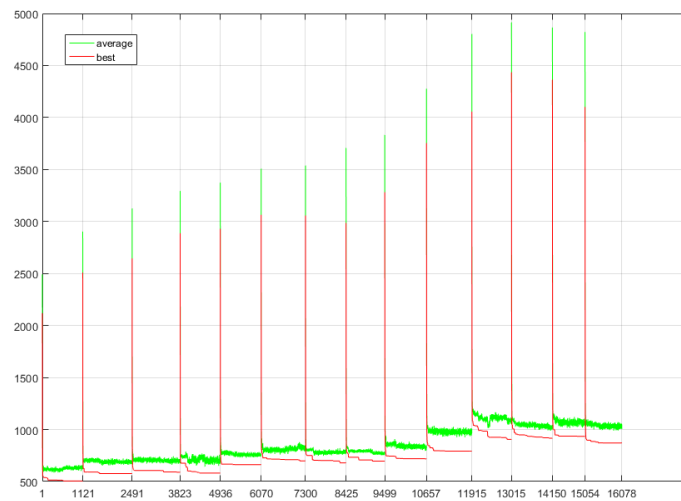


Figure 7. The convergence of each time slice for 'c100' problem

4.3. Convergence analysis of different time slices

In this section, we discuss the convergence of the genetic optimization algorithm in a dynamic environment. Here, we consider an example of problem 'c100'. Figure 7 shows the convergence of each time slice of c100, where the horizontal axis represents the number of iterations with a run time of 30 seconds, the vertical axis represents the individual fitness, the green curve represents the average fitness, and the red curve represents the optimal fitness of the population.

It is possible to conclude that an optimization result has been obtained before the end of the execution time result. Compared with Abdallah's experimental method, the method used in this paper can obtain a better solution in a short time, which also confirms the effectiveness of the experimental method.

5. Conclusions

In this paper, DVRP was solved by using an enhanced GA that contained three proposed modifications. The first modification was the genetic selection, which includes a modified tournament selection and elitist strategy. The second was that two different crossover strategies were adopted to increase the diversity of the population during the crossover. The third was that penalty factors were introduced to assess individual fitness while the near distance priority service principle is considered. In addition, a paired-t test is applied to show that there are statistically significant differences between the enhanced GA with penalty factors and other heuristic approaches according to solution quality.

There are various avenues for future research based on our approach, such as using larger problem instances and further evaluating the enhanced GA's performance. In addition, our approach is considering solving DVRP with a time window and/or solving DVRP with pickup and delivery.

Acknowledgments

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