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A New Method for Generating Initial Solutions of Capacitated Vehicle Routing Problems

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Abstract

In vehicle routing problems, the initial solutions of the routes are important for improving the quality and solution time of the algorithm. For a better route construction algorithm, the obtained initial solutions must be basic, fast, and flexible with reasonable accuracy. In this study, initial solutions are introduced to improve the final solution of the Capacitated Vehicle Routing Problem based on a method from the literature. Using a different formula for addressing the gravitational forces, a new method is introduced and compared with the previous physics inspired algorithm. By using the initial solutions of the proposed method and using them as the initial routes of the Record-to-Record and Simulated Annealing algorithms, it is seen that better results are obtained when compared with various algorithms from the literature. Also, in order to fairly compare the algorithms executed on different machines, a new comparison scale for the solution quality of vehicle routing problems is proposed that depends on the solution time and the deviation from the best known solution. The obtained initial solutions are then input to Record-to-Record and Simulated Annealing algorithms to obtain final solutions. Various test instances and CVRP solutions from the literature are used for comparison. The comparisons with the proposed method have shown promising results.

1. INTRODUCTION

The vehicle routing problem (VRP) is a well-known combinatorial optimization problem that is a technical implementation of operations research in logistics systems. The new algorithms, technology and industry are developed for exact or approximate solutions of VRPs for the effective management of the distribution of goods and services by concerning the optimal design of routes to be used by a fleet of vehicles to serve a set of customers [1].

As the software capabilities increase, more complex variants of VRPs are getting more attention [2]. For instance, in capacitated VRP (CVRP), a homogeneous fleet of vehicles is available and the only constraint is the vehicle capacity [1]. In VRP with time windows, customers must be served within a specified time interval. As the VRP is a hard combinatorial problem, exact algorithms can solve relatively small instances and their computational times are highly variable [3-5]. Mathematical programming techniques to solve combinatorial optimization problems cannot be sufficiently effective. Therefore, researchers have focused on intuitive approaches for solving these problems. In the literature, quite a number of heuristic algorithm approaches and applications are located. For instance, exact methods such as branch and bound, dynamic programming, integer programming can be computationally expensive for even small instances. Thus, heuristic algorithms are often used for the solution of practical instances [6, 7].

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The metaheuristics like tabu search, simulated annealing (SA), variable neighborhood search provide a global search strategy for exploring the solution space [8]. These algorithms are developed from nature to solve highly complex problems as VRP.

Recently, global optimization approach based on physics has become popular. It is a branch of metaheuristics directly motivated from the physics laws. Physics-based algorithms are inspired by the Newtonian gravity and the laws of motion [9] and have been called by different names inspired by physics. Artificial physics optimization (APO) can be considered as one of the first physics-based algorithm examples. The implementations of APO and its improvements are applied to multidimensional numeric benchmark functions and the simulation results confirm APO is effective [10]. Central force optimization (CFO) of Formato, [12], gravitational search algorithm (GSA) of [9, 11], gravitation field algorithm [13], extended artificial physics optimization [10, 14, 37] are also important examples of physics inspired methods. For global optimization problems, these methods are used for improving the solution. For instance, APO has been used for controlling the multi-robot systems in engineering applications. The extended artificial physics optimization (EAPO) is proposed for multidimensional search and optimization [15]. Also, a heuristic algorithm is developed and used to optimize a 10 bar plane truss in analogy with the closed universe theory which is based on the idea that the energy of the attraction of bodies overcomes the kinetic energy generated by the initial universe explosion [16]. Ding et. al [17] have proposed extended central force optimization algorithm derived from CFO of Formato [12].

Rashedi et al. [11] proposed the gravitational search algorithm (GSA) which provides an iterative method that simulates mass interactions and moves through the search space under the effect of the gravitation. They also applied that theory for allocation of static voltage ampere reactive compensator (SVC) [9]. Later, Sarafrazi et al. [18] improved the GSA performance by using a new operator originating from astrophysics. Hassanzadeh et al. [19] used GSA for multi-objective optimization problems. Chatterjee et al. [20] used GSA and modified particle swarm optimization methods to make the array of the concentric ring array antenna thinner. Duman et al. [21] applied GSA to power systems by solving the constrained economic load dispatch problems used to determine the optimum electrical power of the committed power generation units. Zheng et al. [13] proposed the gravitation field algorithm (GFA) derived from the famous astronomy theory about planetary formation known as solar nebula theory disk model. They used GFA for clustering genes obtained from experimental data.

The above physics-inspired optimization algorithms are not applied to TSP and VRP. The classical heuristics in VRP are classified in three groups: constructive, improvement and two-phase heuristics. Also, two-phase heuristics are divided into two classes: cluster-first-route-second and route-first-cluster-second [6]. Also, an extensive literature of heuristic algorithms in VRPs are discussed by Cordeau et al. [3]. Shin and Han [22] proposed an algorithm which is called centroid based heuristic algorithm as a solution approach for CVRP. This approach consists of three stages and was tested with Augerat test instances. This approach results better than sweep algorithm. Initial solutions are important for the performance of the algorithm. Thus, choosing a good candidate for the initial solution will improve the VRP solution. Karagül et al. [23, 24] introduced a physics-based optimization algorithm for obtaining initial solutions of VRP. Vidal et al. [25] proposed a variant clustered VRP that uses genetic algorithms and iterated local search algorithm for obtaining the initial solutions. Guimarans et al. [26] proposed a methodology based on the variable neighborhood search metaheuristic in which Constraint Programming and Lagrangean Relaxation methods are applied to the CVRP in order to improve the algorithm's efficiency. Also, Guimarans et al. [27] presented an original hybrid approach to solve the CVRP. The approach combines the Probabilistic Algorithm with Constraint Programming (CP) and Lagrangian Relaxation (LR). The efficiency of both [26, 27] are analyzed by testing some well-known CVRP benchmarks of Augerat et al.

Cordea et al. [3] expressed the features of a good VRP solution as accuracy, speed, simplicity and flexibility. Thus, in our study, a physics based algorithm is proposed and analyzed considering these four basic features.

2. MATERIALS AND METHOD

2.1. Background

Newton's law of universal gravitation is given as [28]:

$$F = G\frac{m_1 \cdot m_2}{r^2}, \quad i = 1, 2, ..., n \tag{1}$$

where F is directly proportional with the product of the mass of the objects and inversely proportional with the square of the distance between the centers of mass of the objects. The idea in this study is to use this gravitational basic theorem for the CVRP.

As can be seen in the literature given above, physics based approaches are used with the original equation (1) or with small differences. In our proposed method, there are two features different from other physics based approaches. First of all, our intuition is based on the physics law but the proposed mathematical formula is a variant of the physics formula. The formula is especially designed from the original physics formula to solve optimization problems for the VRP.

2.2. Proposed Initial Solution Approach

Karagül, Tokat and Aydemir [23, 24] defined the depot-vertex mass forces, the mass gravitational constants and vertex–vertex mass forces respectively as

$$X_i^c = \frac{q_i \cdot d_{1i}}{\sum q_j}, \; i = 2, ..., n; \; j = 2, ..., n \tag{2}$$

$$A_{ij} = \frac{q_j}{(q_i + q_j)}, \; i = 2, ..., n-1; \; j = i+1, ..., n; \; A_{ij} = A_{ji}, A_{ii} = 0 \tag{3}$$

$$X_{ij} = \frac{(1 - \mathrm{A_{ij}}) * d_{1\mathrm{i}} + \mathrm{A_{ij}} * d_{1j}}{d_{ij}} \; i = 2, ..., n-1; \; j = i+1, ..., n \tag{4}$$

In (2), d_{ij} is the distance between ith vertex and jth vertex. The vertex with index 1 is the depot. Thus, d_{1j} is the distance of each customer from the depot. In (2), q_i is the demand of each customer and for the depot q_1=0. X_i^c is the center-vertex mass force which is the mass force between ith vertex and the depot. It gives the amount of interaction between the customer and the depot. The main formula of the algorithm is given in (4) where X_{ij} is the vertex-vertex mass force which defines the mass force between ith and jth vertices.

When the X_i^c value in (2) is smaller, this means a larger gravitational force. On the other hand, X_{ij} values in (4) is proportional with the gravitational force. For the algorithm, higher gravitational force between a vertex and a depot has priority to enter the solution space. Therefore, lower X_i^c and higher X_{ij} values increase the priority of the related vertex to enter the solution space.

In this study, (2) and (3) are used as in [23, 24] whereas X_{ij} is proposed as follows

$$X_{ij} = (1 - \mathrm{A_{ij}}) * \mathrm{d_{1i}} + \mathrm{A_{ij}} * \mathrm{d}_{1j} - d_{ij}, \; i = 2, ..., n-1; j = i+1, ..., n \tag{5}$$

Using the calculated X_{ij} and X_i^c values, the Mass-Force Matrix in Table 1 is formed. As can be seen in Table 1, the diagonal of the table is empty. Therefore, in order to fulfill the table, the first row or first column of Table 1 is placed to the diagonal of the matrix in Table 1. Then the Mass-Force Matrix is prepared as in Table 2 for the solution of the process.

Table 1. *Mass-force matrix representatives*

q_i	0	1	2	3	4	5	6
Vertex	1	2	3	4	5	6	7
1	-	X_2^c	X_3^c	X_4^c	X_5^c	X_6^c	X_7^c
2	X_2^c	-	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}
3	X_3^c	X_{23}	-	X_{34}	X_{35}	X_{36}	X_{37}
4	X_4^c	X_{23}	X_{34}	-	X_{45}	X_{46}	X_{47}
5	X_5^c	X_{23}	X_{34}	X_{45}	-	X_{56}	X_{57}
6	X_6^c	X_{23}	X_{34}	X_{45}	X_{56}	-	X_{67}
7	X_7^c	X_{23}	X_{34}	X_{45}	X_{56}	X_{67}	-

Table 2. *The prepared solution for mass-force matrix representatives*

q_i	0	1	2	3	4	5	6
Vertex	1	2	3	4	5	6	7
1	-	X_2^c	X_3^c	X_4^c	X_5^c	X_6^c	X_7^c
2	X_2^c	X_2^c	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}
3	X_3^c	X_{23}	X_3^c	X_{34}	X_{35}	X_{36}	X_{37}
4	X_4^c	X_{23}	X_{34}	X_4^c	X_{45}	X_{46}	X_{47}
5	X_5^c	X_{23}	X_{34}	X_{45}	X_5^c	X_{56}	X_{57}
6	X_6^c	X_{23}	X_{34}	X_{45}	X_{56}	X_6^c	X_{67}
7	X_7^c	X_{23}	X_{34}	X_{45}	X_{56}	X_{67}	X_7^c

The proposed constructional initial routing algorithm flow charts are given in Figure and Figure 2. Also, the solution steps are given as follows:

Preparation Phase

1. Calculate Depot-Vertex Mass Forces.
2. Calculate Mass Gravitational Constants
3. Calculate Vertex –Vertex Mass Forces using (5)
4. Create Mass Force Matrix as in Table 1.
5. Assign Depot-Vertex Mass Force values to diagonal cells in Mass Force Matrix as in Table 2.

Implementation Phase

6. Choose min value in first row (min value sign to nearest depot and customer) then close the chosen row r_1 and column c_1
7. Go to row c_1, find max value (which gives the nearest customer) c_2. Then add vertex c_2 to the route.
8. Close row c_1 and column c_2.
9. Repeat 7 until all rows are closed. Then get one TSP solution.
10. Other *n* TSP solutions are obtained from mass-force matrix from each row by ordering the vertices in decreasing order at each row.
11. Considering the capacity constraints (Q), all (n+1) TSP solutions are converted into CVRP routes.
12. From (*n*+1) CVRP routes, choose route structure with minimum Total Cost.

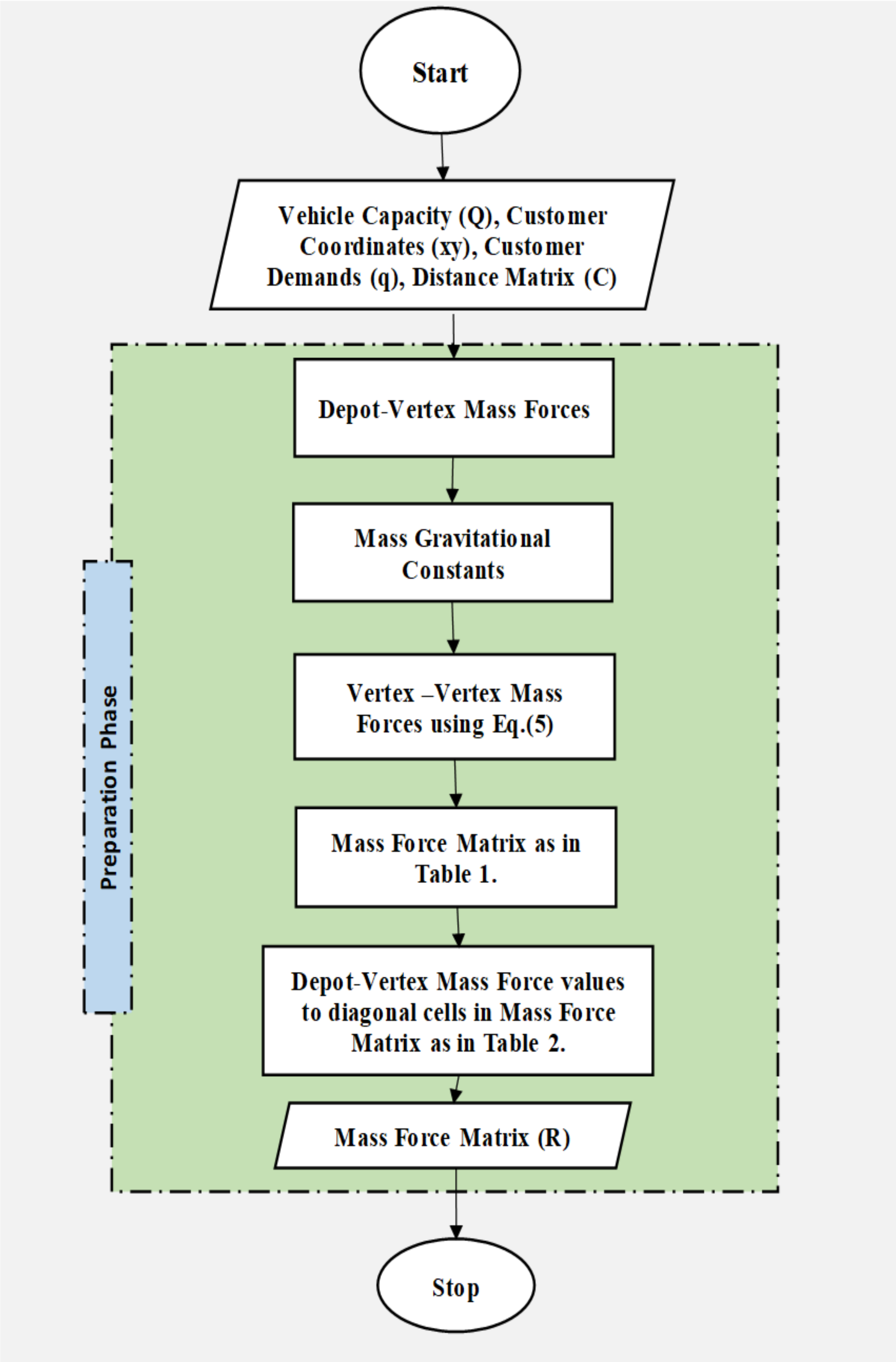

Figure 1. *Proposed constructional initial routing algorithm flow chart: Preparation phase*

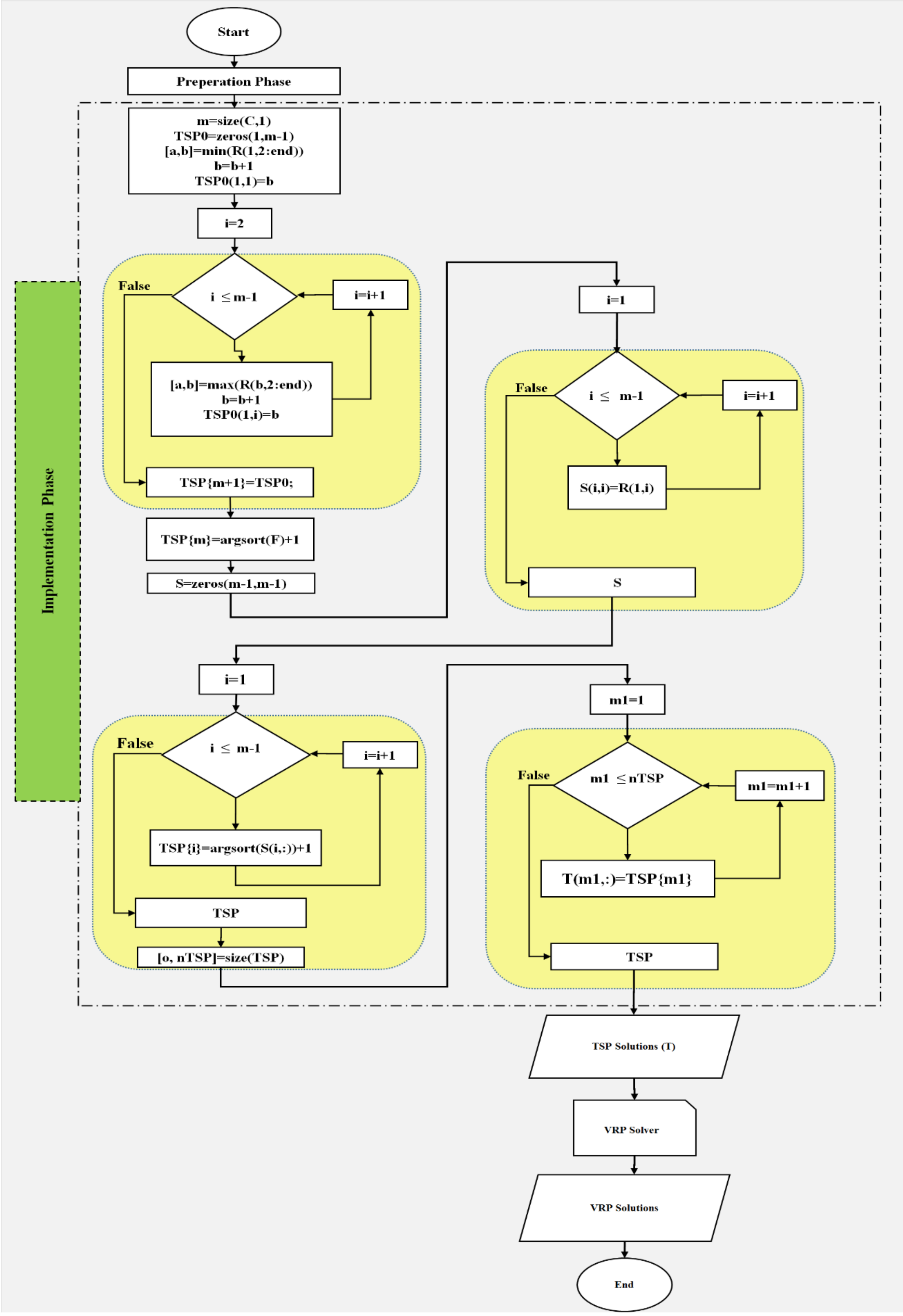

Figure 2. *Proposed constructional initial routing algorithm flow chart: Implementation phase*

Karagül, Tokat and Aydemir [24] suggested a small tutorial and a sample solution for the first approach from which the detailed information about the implementation of the method can be obtained.

3. COMPUTATIONAL EVALUATION

All testing problems (A, B, P, M, F and X CVRP test instances) downloaded from the website (http://vrp.atd-lab.inf.puc-rio.br/index.php/en/). As the first test group, A, B and P problems are used that are suggested by Aguerat et al. and well-known in the literature. In the second test group, 20 of 100 X CVRP test instances of Uchoa et al. are used [29] where a detailed description of all the VRP test problems are given. It is claimed by Uchoa et al. that A, B, P, M, F test instances are not related to real-life problems and thus X CVRP test instances are proposed to meet the gap between simulation test instances and real-life problems [29].

In Table 3, the average results for initial solutions of the related test instances are given where IS1 is the KTA initial solutions for A, B and P test instances presented by [23, 24] in which basic GA with mutation rate 0.1 and crossover rate 0.9 with 1000 generation is used. IS2 is the initial solutions of the newly proposed Karagül-Kay-Tokat (K2T) approach. IS3 and IS4 are the initial solutions of [26] and [27], respectively. In Table 3, Instance is the name of the test instance in the literature, BKS is the best known solution, %Dev is the solution deviation from BKS and T is the solution time in terms of seconds. Table 3 is analyzed using Fig.3-6. In Fig 3, Fig 4 and Fig 5, comparisons are drawn using absolute values of deviations. Fig 3 shows the comparison of the initial solutions of KTA and K2T for test instances A. In this group, there are 27 problems, K2T solutions 17 out of 27 which is better than KTA solutions. K2T and KTA average deviations are 34.87% and 37.95%, respectively which are far from BKS. Also, Fig 4 shows the same comparisons of KTA and K2T initial solutions for test instances B. There are 23 problems and K2T initial solutions are better than KTA in 16 out of 23 problems. K2T and KTA average deviations are 25.42% and 32.10%, respectively. Same results are given in Fig 5 test instances P. K2T initial solutions are better than KTA solutions for 17 out of 24 problems. The average deviations from the BKS for K2T and KTA are 23.36% and 31.45%, respectively. Problem test instances based comparisons showed that K2T algorithm has a superiority against KTA algorithm.

The comparisons of IS1, IS2, IS3 and IS4 methods for different problem sets are given in Fig 6. It can be seen that for all problem groups (A, B, P, E, F and M) IS4 method generates best initial solutions. Also, IS2 method generates the second best results for all problems (A, B, P, E, F and M). However, for problem group X there is not any chance of comparison. The third best results are obtained for IS1 and the worst results are obtained for IS3. When the initial solutions are compared in terms of amount of time, only IS1 and IS4 are compared as there is not enough information about IS1 and IS3. It can be seen in Table 3 that IS4 is superior than IS1.

The IS3 and IS4 tests are taken from the literature. They have been done in a server with Intel Xeon Quad-Core i5 2.66 GHz server 16GB RAM. IS1 and IS2 tests have been done in Windows 8.1 Pro operating system, Intel(R) Core(TM) i7-4800MQ CPU 2.70 GHz, 16 MB RAM, 64 Bit machine.

The KTA and K2T tests are simulated using Windows 8.1 Pro operating system, Intel(R) Core(TM) i7-4800MQ CPU 2.70 GHz, 16 MB RAM, 64 Bit machine, it has used only one core. For both KTA and K2T, Matlab with Matlog toolbox are used [30, 31]. In K2T, on the other hand, improvement solution is getting with the Record-to-Record (RTR) [32] and Simulated Annealing (SA) [33] algorithms on VRPH C library [34] with the default parameters. Distances are not rounded in initial phase, but are rounded in improvement phase.

Table 3. *Average values of test instances for initial solutions*

		Instance	A	B	P	E*	F	M	X
		BKS	**1042**	**964**	**587**	**687**	**708**	**1084**	**71632**
Solution Approaches	**IS1**	**Distance**	1437.25	1275.42	780.51	-	-	-	-
		Dev (%)	-37.95	-32.10	-31.45	-	-	-	-
		T (sec)	0.12	0.13	0.13	-	-	-	-
	IS2	**Distance**	1398.58	1205.79	727.00	966.23	1026.15	1533.60	83711.30
		Dev (%)	-34.87	-25.42	-23.36	-40.02	-55.10	-40.84	-23.11
		T (sec)	0.10	0.10	0.10	0.12	0.14	0.50	112.00
	IS3	**Distance**	1807.44	1749.22	965.14	1281.18	1106.33	2257.40	-
		Dev (%)	-72.93	-83.63	-60.78	-76.47	-56.34	-104.66	-
		T (sec)	0.04	-	0.04	-	-	-	-
	IS4	**Distance**	1106.63	1010.26	643.43	788.27	733.00	1171.80	-
		Dev (%)	-6.39	-4.78	-8.92	-8.58	-3.58	-8.14	-
		T (sec)	0.01	0.01	0.01	0.02	0.03	0.18	-

ISi: Initial Solutions of S_i
IS1: Karagul-Tokat-Aydemir [23, 24]
IS2: Karagul-Kay-Tokat (proposed)
*:Different number of problem and BKS average 726 for IS4
IS3: Guimarans et al. [27]
IS4: Guimarans et al. [26]

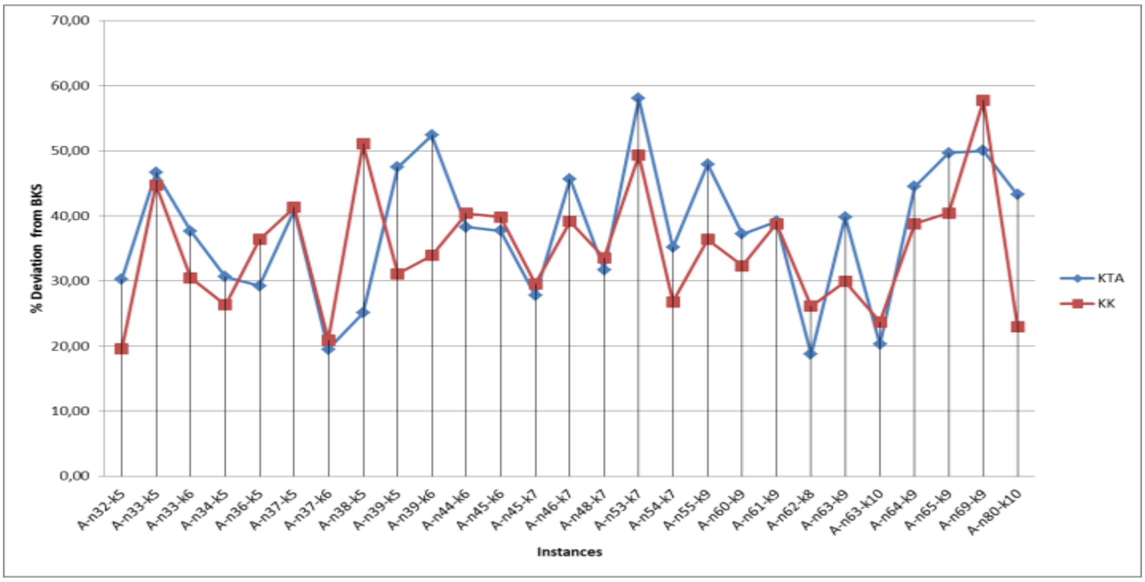

Figure 3. *Comparison of KTA and K2T for A*

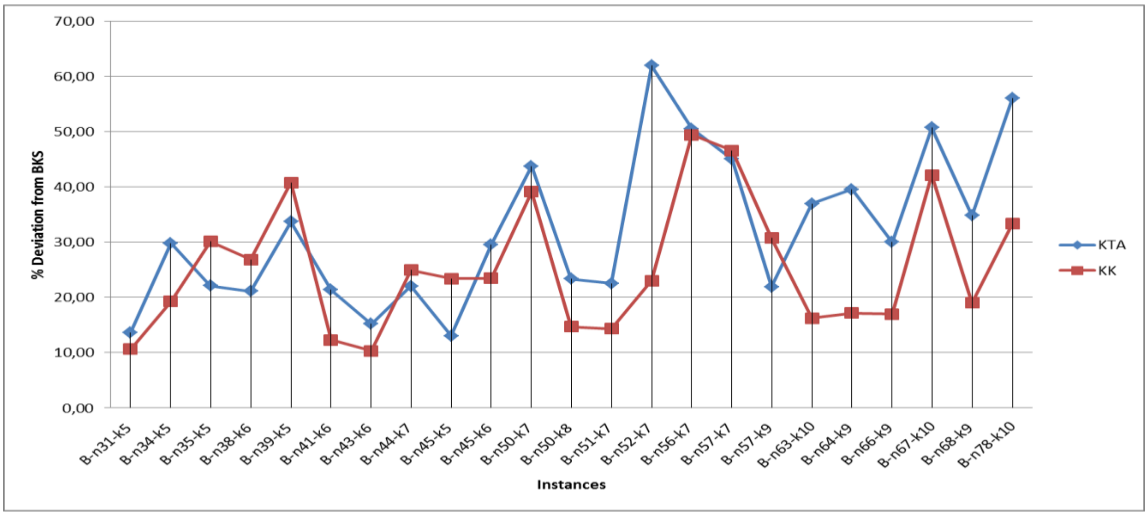

Figure 4. *Comparison of KTA and K2T for B*

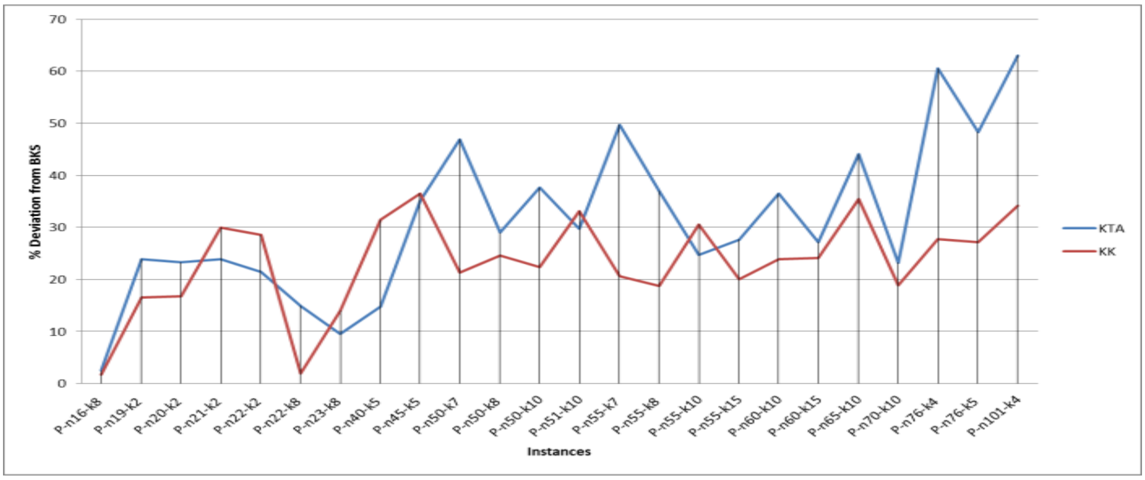

Figure 5. *Comparison of KTA and K2T for Group P*

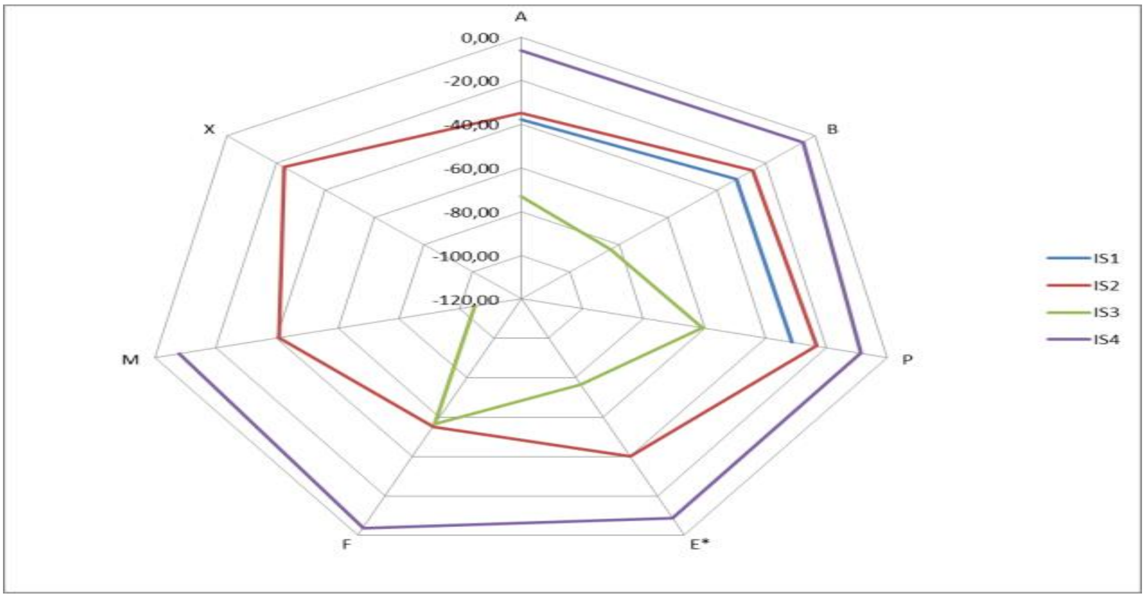

Figure 6. *Comparison of IS1, IS2, IS3 and IS4 for all instances*

The initial solutions of S1, S2, S3 and S4 are analyzed in Fig.3-6. Using the obtained initial solutions, the final VRP solutions of the related approaches are given in Table 4. These approaches are called S1-S9, respectively. KTA with genetic algorithm (GA) is S1 [23, 24], the proposed K2T with RTR is S2, the proposed K2T with SA is S3, constraint programming and Lagrangian relaxation in metaheuristic of Guimarans et al. is S4 [26]. The probabilistic and constraint programming and Lagrangian relaxation method of Guimarans et al. is S5 [27]. The split approach that is a GA based approach is S6 [5, 35], the multi-start approach is S7 [5, 35], iterated local search based metaheuristic algorithm (ILS-SP) is S8 and unified hybrid genetic search (UHGS) is S9. The S8 and S9 tests have been conducted on a Xeon CPU with 3.07 GHz and 16 GB of RAM, running under Oracle Linux Server 6.4 [29].

The average results of the A, B, P and X test instances are given in Table 4. A, B and P group problem sets are solved by S1-S7. But X instances are just solved by only S2, S3, S8 and S9. For a detailed analysis of each test instance of a group, appendices are given where the Initial solution comparisons are given appendices 1-4 whereas improved solution comparisons are given in appendices 5-8. The initial and improved solutions of KTA with GA are given in appendices 9-11.

Table 4. *Improved solutions for different methods*

Solution Approaches			Distances							
Instance	**BKS**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
A	**1042**	1121.6	1056.1	1059.3	1045.7	1047.0	1045.6	1062.1	-	-
B	**964**	1011.7	972.7	977.0	972.8	968.0	966.0	979.5	-	-
P	**587**	628.4	590.6	594.5	568.7	605.3	572.7	582.6	-	-
X	**71632**	-	72680.8	75105.6	-	-	-	-	72012.1	71649.0
Solution Approaches			**Deviations From BKS**							
Instance	**BKS**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
A	**1042**	-7.15	-1.24	-1.62	-0.31	-0.56	-0.44	-2.10	-	-
B	**964**	-4.37	-0.86	-1.23	-0.86	-0.40	-0.15	-1.55	-	-
P	**587**	-6.33	-0.61	-0.33	-0.30	-0.21	0.07	-1.63	-	-
X	**71632**	-	-1.56	-5.66	-	-	-	-	-0.56	-0.03
Solution Approaches			**Solution Times (seconds)**							
Instance	**BKS**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
A	**1042**	181.19	0.54	0.91	1181	610	300	300	-	-
B	**964**	180.38	0.63	0.85	-	763	300	300	-	-
P	**587**	148.34	0.52	0.98	1836	4043	300	300	-	-
X	**71632**	-	17.34	172.90	-	-	-	-	**139.66**	**166.43**

S1: Karagul-Tokat-Aydemir GA [23, 24]
S2: Karagul-Kay-Tokat with RTR
S3: Karagul-Kay-Tokat with SA
S4: Guimarans et al. [27]
S5: Guimarans et al. [26]
S6: Battara et al. [5, 35] – Split
S7: Battara et al. [5, 35] – Multistart
S8: Uchoa et al. [16]- ILS-SP average
S9: Uchoa et al. [29] - UHGS average
S6: Battara et al. [5, 35] – Split

When deviation from BKS are analyzed in Table 4, it can be seen that the order of precedence of success is as S4, S6, S5, S2, S3, S7 and S1 for Group A; S6, S5, S3, S4, S2, S7 and S1 for Group B; S6, S5, S4, S3, S2, S7, and S1 for Group P; and S9, S8, S2, and S3 for Group X. When the amount of solution times is compared it can be seen that the order of precedence for success is S2, S3, S1, and others.

4. NEW COMPARISON TECHNIQUE PROPOSAL FOR VRP

As can be seen in Table 4, for comparing different methods, the deviation from BKS or amount of solution times are considered separately. To compare the methods considering both quantities at the same time, a new scale based on deviation from BKS and amount of solution time is proposed. Thus, it is assumed that there are two different solution techniques to be compared:

Si: Method *i* for VRP solution (*i*=1,2)

Si(dev): deviation from BKS/Optimal for *Si* (*i*=1,2)

T(Si): solution time for *Si* (*i*=1,2)

Therefore, a new scale called Solution Quality Parameter (SQP) is defined as:

$$SQP = \left| \left(\frac{S1(dev)}{S2(dev)} \right) \left(\frac{T(S1)}{T(S2)} \right) \right| \tag{6}$$

Table 5. *Algorithm examples for CVRP with computer hardware skills [36]*

					T1		**T2**		**T3**
		M1	**M2**	**M3**	**A**		**B**		**C**
PN	**BKS**	**A**	**B**	**C**	**R. Time**	**S. Time**	**R. Time**	**S. Time**	**Time**
C1	524,61	524,61	524,61	524,61	24	12	2	0,4	13
C2	835,26	844,42	835,26	849,77	57	28	11	2	19
C3	826,14	829,4	830,02	844,72	101	49	30	5	41
C4	1028,42	1048,89	1028,42	1059,03	223	108	211	38	132
C5	1291,45	1323,89	1305,4	1302,33	413	200	677	123	201
C6	555,43	555,43	555,43	555,43	30	15	24	4	22
C7	909,68	917,68	909,68	909,68	69	33	20	4	39
C8	865,94	867,01	865,94	866,32	115	56	57	10	103
C9	1162,55	1181,14	1162,55	1181,6	295	143	307	56	238
C10	1395,85	1428,46	1395,85	1417,88	517	251	840	153	419
C11	1042,11	1051,87	1042,11	1042,11	93	45	61	11	319
C12	819,56	819,56	819,56	847,56	88	43	31	6	190
C13	1541,14	1546,2	1545,92	1542,86	160	78	127	23	63
C14	866,37	866,37	866,37	866,37	99	48	43	8	49
Average	**976,04**	**986,07**	**977,65**	**986,45**	**163,14**	**79,21**	**174,36**	**31,67**	**132,00**

R. Time: Reported Time S. Time: Scaled Time PN: Problem Name

A: PSO-A&K B:ACO-Y C: HEMA

For comparing the SQP results, a comparison technique given in [36] is also considered and given in Table 5 where the scaled times are calculated with respect to the specifications of the computers.

The solution performances in terms of scaled times and solution qualities are given as Best(M1-M2-M3) in Table 6. The pairwise SQP values are given in SQP (M1/M2), SQP(M1/M3), SQP(M2/M3) columns. The superior of the pairwise comparison is given in Best(M1-M2), Best(M2-M3) and Best(M1-M3) columns. It is seen from the comparison tables that similar results were obtained with calculations based on the SQP and the specifications of the computers as in [36]. However, the scaled time to be created by obtaining the technical specifications of computers as in [36] is difficult to obtain and rather cumbersome in practical solutions. As can be seen in [36], the "scaled time" cannot be calculated for all. Thus, SQP can be recommended as a more practical and feasible method when compared with the method given in [36].

If any method has zero deviation from BKS/Optimal value then the related Si(dev) is taken as 0.001 considering that the precision for BKS/Optimal values is 0.01. If SQP is equal to 1, this means indifference at S1 and S2 solutions. If SQP>1, then S1 solution is worse than S2, and if SQP<1, then S1 solution is better than S2. The SQP results of the one to one comparisons of the methods are given in Table 7 for different test groups A, B, P and X. It can be seen that S2 has superior SQP values for all test groups.

Table 6. *SQP Example Comparisons with Computer Hardware Skills*

P. Name	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
M1(dev)	0,001	-9,15	-3,25	-20,46	-32,43	0,001	-7,99
M2(dev)	0,001	0,001	-3,879	0,001	-13,949	0,001	0,001
M3(dev)	0,001	-14,509	-18,579	-30,609	-10,879	0,001	0,001
Best(M1-M2-M3)	M2>M1>M3	M2>M1>M3	M2>M1>M3	M2>M1>M6	M2>M3>M1	M2>M1>M3	M2>M3>M2
SQP(M1/M2)	12,00	-47460,27	2,83	-21633,11	1,42	1,25	-27596,55
SQP(M1/M3)	1,85	1,89	0,43	1,13	6,13	1,36	-14152,08
SQP(M2/M3)	0,15385	-0,00004	0,15277	-0,00005	4,31864	1,09091	0,51282
Best(M1-M2)	M2	M2	M2	M2	M2	M2	M2
Best(M1-M3)	M3	M3	M1	M3	M3	M3	M3
Best(M2-M3)	M2	M2	M2	M2	M3	M3	M2
P. Name	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**
M1(dev)	-1,069	-18,589	-32,609	-9,759	0,001	-5,059	0,001
M2(dev)	0,001	0,001	0,001	0,001	0,001	-4,779	0,001
M3(dev)	-0,379	-19,049	-22,029	0,001	-27,999	-1,719	0,001
Best(M1-M2-M3)	M2>M3>M1	M2>M1>M3	M2>M3>M1	M2>M3>M1	M2>M1>M3	M3>M2>M1	M2>M1>M3
SQP(M1/M2)	-2156,75	-17862,39	-20070,06	-14878,48	2,84	1,33	2,30
SQP(M1/M3)	3,15	1,21	1,83	-2845,10	0,00	7,47	2,02
SQP(M2/M3)	-0,0015	-0,0001	-0,0001	0,1912	0,0000	5,6043	0,8776
Best(M1-M2)	M2	M2	M2	M2	M2	M2	M2
Best(M1-M3)	M3	M3	M3	M3	M1	M3	M3
Best(M2-M3)	M2	M2	M2	M2	M2	M3	M2

Table 7. *The SQP results of the one to one comparisons of the methods*

Group A	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
S1	-	1916.4	877.1	3.50	3.79	9.74	2.06	-	-
S2		-	**0.4577**	**0.0018**	**0.0020**	**0.0051**	**0.0011**	-	-
S3			-	**0.0040**	**0.0043**	**0.0111**	**0.0023**	-	-
S4				-	1.08	2.78	0.5880	-	-
S5					-	2.57	0.5436	-	-
S6							0.2114	-	-
Group B	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
S1	-	1443.6	751.4	-	2.58	17.52	1.69	-	-
S2		-	**0.5205**	-	**0.0018**	**0.0121**	**0.0012**	-	-
S3			-	-	**0.0034**	**0.0233**	**0.0022**	-	-
S5					-	6.79	0.6548	-	-
S6						-	0.0965	-	-
Group P	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
S1	-	2964.8	2895.9	1.72	1.09	-46.56	1.91	-	-
S2		-	**0.9768**	**0.0006**	**0.0004**	**-0.0157**	**0.0006**	-	-
S3			-	**0.0006**	**0.0004**	**-0.0161**	**0.0007**	-	-
S4				-	0.6339	-27.12	1.12	-	-
S5					-	-42.78	1.76	-	-
S6						-	-0.0411	-	-
Group X	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
S1	-	-	-	-	-	-	-	-	-
S2	-	-	-	-	-	-	-	**0.0058**	**0.0821**
S3	-	-	-	-	-	-	-	**0.2094**	2.98

5. CONCLUSION

In this study, the improvement of the initial solutions of the routes of a vehicle routing problem is considered. By inspiring from the gravitational forces from physics, a constructional heuristic algorithm is proposed. The proposed method for the initial solutions is basic, flexible with reasonable accuracy and faster than other methods from the literature. Later, final improved solutions are generated by using the initial solutions of the proposed method and using them as RTR and SA initial routes. It is seen that better results are obtained when compared with various algorithms from the literature. The solution quality parameter is calculated using both the solution time and the deviation from the best known solution at the same time. This new parameter is proposed as a new comparison scale for the TSP and VRP. As a further study, derivations of the proposed constructional heuristic algorithm can be used for different variants of VRPs.

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CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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APPENDIXES

A1. Augerat et al. A Instances, KTA (Karagül-Tokat-Aydemir [24], Karagul-Kay-Tokat (K2T), Guimarans et al. A, Guimarans et al. B Initial Solutions [26, 27]

Instances		KTA Approach			K2T Approach			Initial Solution A			Initial Solution B		
P. Name	**BKS**	**Dist**	**Dev**	**T1**	**Dist**	**Dev**	**T2**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**
A-n32-k5	784	1021.5	-30.29	0.083	937.8	-19.62	0.064	1243	-58.55	0.256	840	-7.14	0.018
A-n33-k5	661	969.3	-46.65	0.080	956.7	-44.73	0.066	1185	-79.27	0.018	708	-7.11	0.006
A-n33-k6	742	1021.6	-37.68	0.090	968.0	-30.46	0.068	1289	-73.72	0.013	754	-1.62	0.004
A-n34-k5	778	1016.1	-30.60	0.084	982.8	-26.33	0.064	1259	-61.83	0.014	808	-3.86	0.004
A-n36-k5	799	1032.8	-29.26	0.091	1089.6	-36.37	0.068	1207	-51.06	0.024	838	-4.88	0.004
A-n37-k5	669	942.3	-40.85	0.086	945.5	-41.33	0.069	960	-43.50	0.012	720	-7.62	0.004
A-n37-k6	949	1133.9	-19.48	0.091	1147.8	-20.95	0.074	1393	-46.79	0.020	1018	-7.27	0.004
A-n38-k5	730	913.2	-25.09	0.089	1102.5	-51.03	0.069	1240	-69.86	0.017	790	-8.22	0.022
A-n39-k5	822	1212.3	-47.48	0.087	1077.6	-31.09	0.071	1291	-57.06	0.010	870	-5.84	0.004
A-n39-k6	831	1266.5	-52.41	0.091	1112.8	-33.91	0.077	1523	-83.27	0.014	902	-8.54	0.004
A-n44-k6	937	1295.8	-38.29	0.100	1315.5	-40.39	0.084	1547	-65.10	0.020	980	-4.59	0.003
A-n45-k6	944	1300.1	-37.72	0.107	1319.7	-39.80	0.085	1826	-93.43	0.022	1038	-9.96	0.012
A-n45-k7	1146	1464.3	-27.77	0.112	1484.7	-29.55	0.089	1768	-54.28	0.022	1267	-10.56	0.004
A-n46-k7	914	1331.5	-45.68	0.111	1271.9	-39.16	0.092	1711	-87.20	0.024	986	-7.88	0.004
A-n48-k7	1073	1413.4	-31.72	0.118	1432.9	-33.54	0.095	1840	-71.48	0.025	1114	-3.82	0.004
A-n53-k7	1010	1596.0	-58.02	0.120	1507.8	-49.29	0.099	1841	-82.28	0.030	1072	-6.14	0.005
A-n54-k7	1167	1576.9	-35.12	0.124	1479.7	-26.80	0.105	1883	-61.35	0.051	1238	-6.08	0.005
A-n55-k9	1073	1587.2	-47.92	0.148	1463.2	-36.37	0.118	2074	-93.29	0.034	1105	-2.98	0.005
A-n60-k9	1354	1857.4	-37.18	0.156	1791.4	-32.30	0.125	2224	-64.25	0.037	1407	-3.91	0.006
A-n61-k9	1034	1438.7	-39.14	0.160	1435.2	-38.80	0.129	2045	-97.78	0.034	1075	-3.97	0.014
A-n62-k8	1288	1529.5	-18.75	0.151	1624.3	-26.11	0.124	2344	-81.99	0.033	1352	-4.97	0.008
A-n63-k9	1616	2259.1	-39.80	0.165	2099.5	-29.92	0.134	2275	-40.78	0.039	1387	14.17	0.007
A-n63-k10	1314	1580.4	-20.27	0.171	1625.3	-23.69	0.141	2659	-102.36	0.039	1657	-26.10	0.012
A-n64-k9	1401	2024.0	-44.47	0.160	1944.2	-38.77	0.135	2215	-58.10	0.039	1496	-6.78	0.008
A-n65-k9	1174	1757.0	-49.66	0.175	1648.9	-40.45	0.142	2331	-98.55	0.045	1306	-11.24	0.033
A-n69-k9	1159	1738.9	-50.03	0.179	1827.8	-57.70	0.146	2463	-112.51	0.068	1247	-7.59	0.009
A-n80-k10	1763	2526.0	-43.28	0.216	2168.6	-23.01	0.180	3165	-79.52	0.053	1904	-8.00	0.015
Average	**1042**	**1437.0**	**-37.95**	**0.124**	**1398.6**	**-34.87**	**0.100**	**1807.4**	**-72.93**	**0.038**	**1106.6**	**-6.39**	**0.008**

A2. Augerat et al. B Instances, KTA (Karagül-Tokat-Aydemir [24], Karagul-Kay-Tokat(K2T), Guimarans et al. A, Guimarans et al. B Initial Solutions [26, 27]

Instances		KTA Approach			K2T Approach			Initial Solution A			Initial Solution B		
P. Name	**BKS**	**Dist**	**Dev**	**T1**	**Dist**	**Dev**	**T2**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**
B-n31-k5	672	763.84	-13.67	0.081	743.51	-10.64	0.069	1121	-66.82	-	685	-1.93	0.002
B-n34-k5	788	1022.70	-29.78	0.083	939.66	-19.25	0.066	1101	-39.72	-	799	-1.40	0.002
B-n35-k5	955	1166.00	-22.09	0.083	1242.30	-30.08	0.069	1460	-52.88	-	998	-4.50	0.002
B-n38-k6	805	974.89	-21.10	0.093	1021.30	-26.87	0.074	1393	-73.04	-	830	-3.11	0.003
B-n39-k5	549	734.06	-33.71	0.100	772.92	-40.79	0.072	1072	-95.26	-	581	-5.83	0.003
B-n41-k6	829	1006.00	-21.35	0.102	930.68	-12.27	0.079	1504	-81.42	-	913	-10.13	0.024
B-n43-k6	742	854.68	-15.19	0.107	818.71	-10.34	0.081	1185	-59.70	-	766	-3.23	0.011
B-n44-k7	909	1109.40	-22.05	0.123	1135.60	-24.93	0.089	1622	-78.44	-	954	-4.95	0.003
B-n45-k5	751	848.77	-13.02	0.102	926.47	-23.36	0.080	1337	- 78.03	-	779	-3.73	0.004
B-n45-k6	678	878.40	-29.56	0.107	836.87	-23.43	0.084	1130	-66.67	-	728	-7.37	0.007
B-n50-k7	741	1065.10	-43.74	0.129	1030.90	-39.12	0.097	1728	-133.20	-	785	-5.94	0.004
B-n50-k8	1312	1617.70	-23.30	0.132	1504.50	-14.67	0.105	1987	-51.45	-	1376	-4.88	0.004
B-n51-k7	1032	1264.30	-22.51	0.123	1180.00	-14.34	0.097	2166	-109.88	-	1043	-1.07	0.009
B-n52-k7	747	1209.30	-61.89	0.126	919.18	-23.05	0.099	1548	-107.23	-	760	-1.74	0.005
B-n56-k7	707	1063.90	-50.48	0.135	1056.20	-49.39	0.106	1711	-142.01	-	738	-4.38	0.005
B-n57-k7	1153	1672.00	-45.01	0.133	1689.90	-46.57	0.106	2208	-91.50	-	1255	-8.85	0.009
B-n57-k9	1598	1948.40	-21.93	0.154	2089.40	-30.75	0.129	2373	-48.50	-	1667	-4.32	0.006
B-n63-k10	1496	2048.30	-36.92	0.182	1739.00	-16.24	0.141	2793	-86.70	-	1558	-4.14	0.007
B-n64-k9	861	1201.60	-39.56	0.166	1008.70	-17.15	0.138	1945	-125.90	-	920	-6.85	0.011
B-n66-k9	1316	1710.70	-29.99	0.180	1539.20	-16.96	0.140	2162	-64.29	-	1418	-7.75	0.013
B-n67-k10	1032	1554.90	-50.67	0.184	1466.60	-42.11	0.150	2039	-97.58	-	1105	-7.07	0.011
B-n68-k9	1272	1714.70	-34.80	0.189	1513.50	-18.99	0.144	2219	-74.45	-	1316	-3.46	0.012
B-n78-k10	1221	1905.00	-56.02	0.227	1513.50	-18.99	0.179	2428	-98.85	-	1262	-3.36	0.013
Average	**963.74**	**1275.42**	**-32.10**	**0.132**	**1205.79**	**-25.42**	**0.104**	**1749.22**	**-83.63**	**-**	**1010.26**	**-4.78**	**0.007**

A3. Augerat et al. P Instances, KTA (Karagül-Tokat-Aydemir [24], Karagul-Kay-Tokat(K2T), Guimarans et al. A, Guimarans et al. B Initial Solutions [26, 27]

Instances		**KTA Approach**			**K2T Approach**			**Initial Solution A**			**Initial Solution B**		
P. Name	**BKS**	**Dist**	**Dev**	**T1**	**Dist**	**Dev**	**T2**	**Dista**	**Dev**	**T**	**Dist**	**Dev**	**T**
P-n16-k8	450	461.32	-2.52	0.069	457.95	-1.77	0.063	534	-18.67	0.020	482	-7.11	0.001
P-n19-k2	212	262.77	-23.95	0.064	247.09	-16.55	0.046	267	-25.94	0.156	-	-	-
P-n20-k2	216	266.29	-23.28	0.055	252.19	-16.75	0.044	266	-23.15	0.003	242	-12.04	0.001
P-n21-k2	211	261.41	-23.89	0.057	274.32	-30.01	0.047	276	-30.81	0.003	236	-11.85	0.001
P-n22-k2	216	262.21	-21.39	0.057	277.64	-28.53	0.047	278	-28.70	0.003	244	-12.96	0.001
P-n22-k8	603	693.09	-14.94	0.081	614.96	-1.98	0.062	687	-13.93	0.009	645	-6.97	0.001
P-n23-k8	529	579.62	-9.57	0.082	602.96	-13.98	0.065	642	-21.36	0.016	560	-5.86	0.001
P-n40-k5	458	525.80	-14.80	0.101	602.11	-31.47	0.074	773	-68.78	0.014	510	-11.35	0.002
P-n45-k5	510	688.95	-35.09	0.104	696.43	-36.56	0.079	827	-62.16	0.015	531	-4.12	0.003
P-n50-k7	554	813.93	-46.92	0.122	671.97	-21.29	0.096	1233	-122.56	0.035	761	-37.36	0.005
P-n50-k8	631	814.03	-29.01	0.129	786.36	-24.62	0.106	1012	-60.38	-	586	7.13	0.003
P-n50-k10	696	958.15	-37.67	0.150	851.81	-22.39	0.118	-	-	-	651	6.47	0.004
P-n51-k10	741	961.51	-29.76	0.148	986.52	-33.13	0.120	1248	-68.42	0.031	777	-4.86	0.005
P-n55-k7	568	850.60	-49.75	0.132	685.14	-20.62	0.107	1302	-129.23	0.025	736	-29.58	0.004
P-n55-k8	588	805.67	-37.02	0.134	698.56	-18.80	0.106	-	-	-	1002	-70.41	0.005
P-n55-k10	694	865.45	-24.70	0.159	906.40	-30.61	0.126	1047	-50.86	0.053	602	13.26	0.005
P-n55-k15	989	1262.80	-27.68	0.206	1187.00	-20.02	0.162	1093	-10.52	-	598	39.53	0.005
P-n60-k10	744	1015.20	-36.45	0.169	921.62	-23.87	0.138	1529	-105.51	0.034	796	-6.99	0.005
P-n60-k15	968	1231.00	-27.17	0.221	1202.00	-24.17	0.180	1761	-81.92	0.052	1015	-4.86	0.006
P-n65-k10	792	1140.90	-44.05	0.183	1072.90	-35.47	0.146	1509	-90.53	0.041	836	-5.56	0.006
P-n70-k10	827	1019.20	-23.24	0.200	982.99	-18.86	0.157	1586	-91.78	0.055	870	-5.20	0.008
P-n74-k4	593	952.07	-60.55	0.145	757.79	-27.79	0.108	1062	-79.09	0.068	667	-12.48	0.012
P-n76-k5	627	929.96	-48.32	0.151	797.47	-27.19	0.119	1177	-87.72	0.042	697	-11.16	0.013
P-n101-k4	681	1110.40	-63.05	0.175	913.82	-34.19	0.141	1124	-65.05	0.156	755	-10.87	0.024
Average	**587.42**	**780.51**	**-31.45**	**0.129**	**727.00**	**-23.36**	**0.102**	**965.14**	**-60.78**	**0.042**	**643.43**	**-8.92**	**0.005**

A4. Uchoa et al. X Instances, Karagul-Kay-Tokat (K2T)

Instances		**K2T Approach**				**Instance**
P. Name	**BKS**	**Distance**	**Dev(%)**	**T2(sec)**	**# of R**	**# of k**
X-n101-k25	27591	38001	-37.73	0.45	26	25
X-n106-k14	26362	28352	-7.55	0.29	14	14
X-n157-k13	16876	19175	-13.62	0.52	13	13
X-n200-k36	58578	66473	-13.48	1.82	36	36
X-n251-k28	38684	44356	-14.66	2.07	28	28
X-n303-k21	21744	34147	-57.04	2.24	21	21
X-n351-k40	25946	39087	-50.65	5.86	40	40
X-n401-k29	66243	79727	-20.36	5.20	29	29
X-n459-k26	24181	34586	-43.03	6.19	26	26
X-n502-k39	69253	74373	-7.39	13.35	39	39
X-n561-k42	42756	55064	-28.79	20.57	42	42
X-n613-k62	59778	95249	-59.34	47.10	62	62
X-n655-k131	106780	111280	-4.21	201.17	131	131
X-n701-k44	82292	95818	-16.44	39.82	44	44
X-n766-k71	114683	141760	-23.61	102.09	71	71
X-n801-k40	73587	83176	-13.03	48.94	40	40
X-n856-k95	89060	98270	-10.34	217.11	95	95
X-n916-k207	329836	350330	-6.21	1175.81	217	207
X-n957-k87	85672	94730	-10.57	252.73	87	87
X-n1001-k43	72742	90272	-24.10	96.74	43	43
Average	**71632.2**	**83711.3**	**-23.11**	**112.00**	**55.2**	**54.65**

# of R: Number of Route # of k: Number of Route in instance

A5. Augerat et al. A Instances, Karagul-Kay-Tokat (K2T) with RTR, Karagul-Kay-Tokat (K2T) with SA, Guimarans et al. A, Guimarans et al. B [26, 27], Battara et al.-Split, Battara et al.-Multistart Final Solutions [5, 35]

Instances		**K2T with RTR**			**K2T with SA**			**Final Solution A**			**Final Solution B**			**Battara-Split**			**Battara-Multistart**		
P. Name	**BKS**	**Dist**	**Dev**	**T1**	**Dist**	**Dev**	**T2**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**
A-n32-k5	784	784	0.00	0.23	796	-1.53	0.39	784	0.00	96.62	784	0.00	3.22	784	0.00	300	827	-5.48	300
A-n33-k5	661	661	0.00	0.26	661	0.00	0.39	661	0.00	42.67	661	0.00	6.80	661	0.00	300	675	-2.12	300
A-n33-k6	742	743	-0.13	0.30	742	0.00	0.38	742	0.00	34.86	742	0.00	8.56	743	-0.13	300	745	-0.40	300
A-n34-k5	778	778	0.00	0.27	795	-2.19	0.41	778	0.00	27.88	778	0.00	8.05	778	0.00	300	793	-1.93	300
A-n36-k5	799	799	0.00	0.32	799	0.00	0.47	799	0.00	524.33	799	0.00	34.82	799	0.00	300	805	-0.75	300
A-n37-k5	669	669	0.00	0.35	669	0.00	0.54	669	0.00	55.76	669	0.00	8.29	669	0.00	300	691	-3.29	300
A-n37-k6	949	955	-0.63	0.33	965	-1.69	0.49	949	0.00	59.67	949	0.00	40.03	949	0.00	300	971	-2.32	300
A-n38-k5	730	738	-1.10	0.35	731	-0.14	0.49	731	-0.14	59.02	730	0.00	53.84	730	0.00	300	751	-2.88	300
A-n39-k5	822	828	-0.73	0.40	826	-0.49	0.57	822	0.00	277.41	822	0.00	33.14	822	0.00	300	841	-2.31	300
A-n39-k6	831	833	-0.24	0.41	835	-0.48	0.56	833	-0.24	554.50	833	-0.24	270.05	831	0.00	300	839	-0.96	300
A-n44-k6	937	937	0.00	0.43	942	-0.53	0.68	942	-0.53	149.39	942	-0.53	426.97	942	-0.53	300	948	-1.17	300
A-n45-k6	944	1009	-6.89	0.43	979	-3.71	0.69	950	-0.64	141.67	953	-0.95	353.10	944	0.00	300	955	-1.17	300
A-n45-k7	1146	1154	-0.70	0.53	1151	-0.44	0.78	1146	0.00	207.30	1146	0.00	156.67	1146	0.00	300	1161	-1.31	300
A-n46-k7	914	914	0.00	0.43	967	-5.80	0.82	914	0.00	265.87	914	0.00	274.06	914	0.00	300	926	-1.31	300
A-n48-k7	1073	1100	-2.52	0.81	1084	-1.03	0.82	1084	-1.03	295.10	1086	-1.21	437.59	1086	-1.21	300	1098	-2.33	300
A-n53-k7	1010	1017	-0.69	0.51	1062	-5.15	1.00	1020	-0.99	1291.31	1017	-0.69	756.24	1010	0.00	300	1032	-2.18	300
A-n54-k7	1167	1179	-1.03	0.62	1199	-2.74	1.05	1167	0.00	321.39	1167	0.00	282.75	1168	-0.09	300	1174	-0.60	300
A-n55-k9	1073	1100	-2.52	0.81	1084	-1.03	0.82	1084	-1.03	295.10	1086	-1.21	437.59	1086	-1.21	300	1098	-2.33	300
A-n60-k9	1354	1372	-1.33	0.77	1364	-0.74	1.17	1354	0.00	1589.65	1358	-0.30	1089.6	1354	0.00	300	1372	-1.33	300
A-n61-k9	1034	1044	-0.97	0.65	1054	-1.93	1.23	1037	-0.29	1796.11	1035	-0.10	931.11	1035	-0.10	300	1045	-1.06	300
A-n62-k8	1288	1347	-4.58	0.77	1308	-1.55	1.34	1290	-0.16	3367.11	1308	-1.55	1390.1	1308	-1.55	300	1328	-3.11	300
A-n63-k9	1616	1618	-0.12	0.69	1635	-1.18	1.29	1629	-0.80	3226.55	1318	18.44	1219.6	1315	18.63	300	1344	16.83	300
A-n63-k10	1314	1330	-1.22	0.91	1321	-0.53	1.30	1318	-0.30	1254.34	1621	-23.36	1161.7	1627	-23.82	300	1645	-25.19	300
A-n64-k9	1401	1440	-2.78	0.67	1432	-2.21	1.44	1431	-2.14	386.78	1418	-1.21	1293.6	1411	-0.71	300	1438	-2.64	300
A-n65-k9	1174	1187	-1.11	0.67	1194	-1.70	1.39	1177	-0.26	1577.88	1178	-0.34	1069.4	1181	-0.60	300	1192	-1.53	300
A-n69-k9	1159	1195	-3.11	0.84	1181	-1.90	1.62	1170	-0.95	3752.35	1175	-1.38	1673.2	1165	-0.52	300	1177	-1.55	300
A-n80-k10	1763	1783	-1.13	1.04	1783	-1.13	2.24	1763	0.00	9145.79	1793	-1.70	2867.5	1785	-1.25	300	1809	-2.61	300
Average	**1042**	**1056**	**-1.24**	**0.54**	**1059**	**-1.62**	**0.91**	**1045**	**-0.31**	**1181**	**1047**	**-0.56**	**610**	**1045**	**-0.44**	**300**	**1062**	**-2.10**	**300**

Final Solution A [26], Final Solution B [27], Battara-Split [5, 35], Battara-Multistart [5, 35]

A6. Augerat et al. B Instances, Karagul-Kay-Tokat (K2T) with RTR, Karagul-Kay-Tokat (K2T) with SA, Guimarans et al. A, Guimarans et al. B [26, 27], Battara et al.-Split, Battara et al.-Multistart Final Solutions [5, 35]

Instances		**K2T with RTR**			**K2T with SA**			**Final Solution A**			**Final Solution B**			**Battara-Split**			**Battara-Multistart**		
P. Name	**BKS**	**Dist**	**Dev**	**T1**	**Dist**	**Dev**	**T2**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**	**Dist**	**Dev**	**T**
B-n31-k5	672	675	-0.45	0.23	672	0.00	0.31	672	0.00	-	672	0.00	16.61	672	0.00	300	673	-0.15	300
B-n34-k5	788	788	0.00	0.33	789	-0.13	0.41	788	0.00	-	788	0.00	24.39	788	0.00	300	788	0.00	300
B-n35-k5	955	955	0.00	0.26	970	-1.57	0.42	955	0.00	-	955	0.00	41.58	955	0.00	300	967	-1.26	300
B-n38-k6	805	805	0.00	0.53	805	0.00	0.48	805	0.00	-	805	0.00	120.94	805	0.00	300	823	-2.24	300
B-n39-k5	549	549	0.00	0.58	572	-4.19	0.49	549	0.00	-	549	0.00	118.31	549	0.00	300	561	-2.19	300
B-n41-k6	829	832	-0.36	0.38	829	0.00	0.53	829	0.00	-	829	0.00	155.88	829	0.00	300	853	-2.90	300
B-n43-k6	742	755	-1.75	0.46	745	-0.40	0.58	742	0.00	-	742	0.00	227.07	742	0.00	300	75	-1.08	300
B-n44-k7	909	930	-2.31	0.61	909	0.00	0.60	909	0.00	-	909	0.00	74.76	909	0.00	300	927	-1.98	300
B-n45-k5	751	755	-0.53	0.43	751	0.00	0.64	751	0.00	-	751	0.00	104.76	751	0.00	300	751	0.00	300
B-n45-k6	678	681	-0.44	0.47	680	-0.29	0.56	707	-4.28	-	679	-0.15	439.55	680	-0.29	300	698	-2.95	300
B-n50-k7	741	741	0.00	0.48	781	-5.40	0.78	741	0.00	-	741	0.00	21.63	741	0.00	300	742	-0.13	300
B-n50-k8	1312	1316	-0.30	0.75	1357	-3.43	0.78	1316	-0.30	-	1320	-0.61	682.76	1314	-0.15	300	1336	-1.83	300
B-n51-k7	1032	1049	-1.65	0.51	1042	-0.97	0.75	1032	0.00	-	1019	1.26	3.12	1016	1.55	300	1027	0.48	300
B-n52-k7	747	747	0.00	0.88	748	-0.13	0.88	747	0.00	-	747	0.00	454.11	747	0.00	300	755	-1.07	300
B-n56-k7	707	710	-0.42	0.74	707	0.00	0.99	717	-1.41	-	713	-0.85	1804.90	710	-0.42	300	721	-1.98	300
B-n57-k7	1153	1157	-0.35	0.89	1174	-1.82	0.95	1186	-2.86	-	1152	0.09	22.21	1140	1.13	300	1148	0.43	300
B-n57-k9	1598	1600	-0.13	0.91	1598	0.00	1.06	1600	-0.13	-	1599	-0.06	1011.77	1599	-6	300	1616	-1.13	300
B-n63-k10	1496	1531	-2.34	0.56	1596	-6.68	1.21	1543	-3.14	-	1515	-1.27	1529.03	1537	-2.74	300	1554	-3.88	300
B-n64-k9	861	878	-1.97	0.89	861	0.00	1.21	871	-1.16	-	894	-3.83	1569.95	861	0.00	300	878	-1.97	300
B-n66-k9	1316	1319	-0.23	0.91	1346	-2.28	1.29	1332	-1.22	-	1321	-0.38	1677.59	1319	-0.23	300	1343	-2.05	300
B-n67-k10	1032	1070	-3.68	0.92	1033	-0.10	1.41	1072	-3.88	-	1044	-1.16	1772.67	1032	0.00	300	1058	-2.52	300
B-n68-k9	1272	1290	-1.42	0.71	1281	-0.71	1.37	1287	-1.18	-	1291	-1.49	2553.68	1293	-1.65	300	1308	-2.83	300
B-n78-k10	1221	1240	-1.56	1.09	1224	-0.25	1.87	1223	-0.16	-	1230	-0.74	3129.89	1228	-0.57	300	1252	-2.54	300
Average	**963.74**	**972.74**	**-0.86**	**0.63**	**976**	**-1.23**	**0.85**	**972.78**	**-0.86**	**-**	**968.04**	**-0.40**	**763.36**	**965.96**	**-0.15**	**300**	**979.52**	**-1.55**	**300**

Final Solution A [26], Final Solution B [27], Battara-Split [5, 35], Battara-Multistart [5, 35]

A7. Augerat et al. P Instances, Karagul-Kay-Tokat (K2T) with RTR, Karagul-Kay-Tokat (K2T) with SA, Guimarans et al. A, Guimarans et al. B [26, 27], Battara et al.-Split, Battara et al.-Multistart Final Solutions [5, 35]

Instances		K2T with RTR			K2T with SA			Final Solution A			Final Solution B			Battara-Split			Battara-Multistart		
P. Name	BKS	Dist	Dev	T1	Dist	Dev	T2	Dist	Dev	T	Dist	Dev	T	Dist	Dev	T	Dist	Dev	T
P-n16-k8	450	450	0.00	0.05	450	0.00	0.07	453	-0.67	0.62	450	0.00	0.05	450	0.00	300	450	0.00	300
P-n19-k2	212	218	-2.83	0.07	218	-2.83	0.13	219	-3.30	0.57	212	0.00	1.18	212	0.00	300	219	-3.30	300
P-n20-k2	216	216	0.00	0.07	216	0.00	0.14	216	0.00	0.95	-	-	-	218	-.93	300	222	-2.78	300
P-n21-k2	211	211	0.00	0.09	211	0.00	0.16	211	0.00	2.75	211	0.00	1.88	211	0.00	300	214	-1.42	300
P-n22-k2	216	216	0.00	0.10	216	0.00	0.17	216	0.00	4.64	216	0.00	1.28	216	0.00	300	218	-0.93	300
P-n22-k8	603	590	2.16	0.11	590	2.16	0.15	603	0.00	1.20	591	1.99	0.08	590	2.16	300	590	2.16	300
P-n23-k8	529	540	-2.08	0.11	534	-0.95	0.17	529	0.00	2.43	529	0.00	4.06	529	0.00	300	534	-0.95	300
P-n40-k5	458	458	0.00	0.47	-	-	-	458	0.00	39.43	458	0.00	9.57	458	0.00	300	464	-1.31	300
P-n45-k5	510	513	-0.59	0.45	510	0.00	0.92	510	0.00	111.05	510	0.00	111.16	510	0.00	300	520	-1.96	300
P-n50-k7	554	561	-1.26	0.50	561	-1.26	0.89	554	0.00	115.43	554	0.00	457.91	556	-0.36	300	571	-3.07	300
P-n50-k8	631	637	-0.95	0.72	629	0.32	0.89	-	-	-	631	0.00	165.18	631	0.00	300	641	-1.58	300
P-n50-k10	696	705	-1.29	0.68	697	-0.14	0.81	700	0.57	375.69	700	-0.57	435.12	698	-0.29	300	712	-2.30	300
P-n51-k10	741	755	-1.89	0.55	760	-2.56	0.82	741	0.00	427.25	747	-0.81	407.24	744	-0.40	300	752	-1.48	300
P-n55-k7	568	575	-1.23	0.54	574	-1.06	0.98	568	0.00	448.47	570	-0.35	835.77	574	-1.06	300	583	-2.64	300
P-n55-k8	588	577	1.87	0.58	576	2.04	1.03	577	1.87	247.69	580	1.36	24.91	577	1.87	300	585	0.51	300
P-n55-k10	694	700	-0.86	0.81	698	-0.58	1.02	700	-0.86	704.90	700	-0.86	606.61	696	-0.29	300	709	-2.16	300
P-n55-k15	989	945	4.45	0.62	953	3.64	0.94	-	-	-	984	0.51	0.73	941	4.85	300	962	2.73	300
P-n60-k10	744	760	-2.15	0.82	744	0.00	1.22	744	0.00	1671.03	750	-0.81	833.72	749	-0.67	300	773	-3.90	300
P-n60-k15	968	978	-1.03	0.72	983	-1.55	1.18	975	-0.72	1023.88	971	-0.31	675.66	972	-0.41	300	988	-2.07	300
P-n65-k10	792	808	-2.02	0.78	792	0.00	1.52	792	0.00	780.61	803	-1.39	1163.26	-	-	-	-	-	-
P-n70-k10	827	840	-1.57	0.73	842	-1.81	1.62	842	-1.81	3108.94	847	-2.42	1616.85	834	-0.85	300	850	-2.78	300
P-n74-k4	593	601	-1.35	0.81	601	-1.35	2.01	594	-0.17	12328.96	593	0.00	3729.72	601	-1.35	300	612	-3.20	300
P-n76-k5	627	630	-0.48	0.83	632	-0.80	1.94	628	-0.16	10784.63	632	-0.80	7111.16	632	-0.80	300	649	-3.51	300
P-n101-k4	681	691	-1.47	1.29	687	-0.88	3.73	682	-0.15	8218.18	684	-0.44	74784.60	-	-	-	-	-	-
Average	**587.42**	**590.63**	**-0.61**	**0.521**	**594.52**	**-0.33**	**0.979**	**568.73**	**-0.30**	**1836.33**	**605.35**	**-0.21**	**4042.51**	**572.68**	**0.07**	**300**	**582.64**	**-1.63**	**300**

Final Solution A [26], Final Solution B [27], Battara-Split [5, 35], Battara-Multistart [5, 35]

A8. Uchoa et al. X Instances, Karagul-Kay-Tokat (K2T) with RTR, Karagul-Kay-Tokat (K2T) with SA, Uchoa et al. ILS-SP, Uchoa et al. UHGS, Final Solutions [29]

Instances		K2T with RTR			K2T with SA			ILS-SP*			UHGS*		
P. Name	BKS	Distance	Dev	T1	Distance	Dev	T1	Distance	Dev	T2	Distance	Dev	T2
X-n101-k25	27591	27767	-0.64	1.91	29506	-6.94	4.27	27591.0	0.00	0.13	27591	0.00	1.43
X-n106-k14	26362	26462	-0.38	1.37	27261	-3.41	4.83	26375.9	-0.05	2.01	26381.8	-0.08	4.04
X-n157-k13	16876	16986	-0.65	3.44	17130	-1.51	10.75	16876.0	0.00	0.76	16876	0.00	3.19
X-n200-k36	58578	59259	-1.16	3.11	60901	-3.97	16.05	58697.2	-0.20	7.48	58626.4	-0.08	7.97
X-n251-k28	38684	39290	-1.57	8.23	40614	-4.99	26.63	38840.0	-0.40	10.77	38796.4	-0.29	11.69
X-n303-k21	21744	22186	-2.03	8.57	24250	-11.53	46.35	21895.8	-0.70	14.15	21850.9	-0.49	17.28
X-n351-k40	25946	26644	-2.69	13.64	28056	-8.13	58.99	26150.3	-0.79	25.21	26014.0	-0.26	33.73
X-n401-k29	66243	67408	-1.76	8.08	68051	-2.73	80.33	66715.1	-0.71	60.36	66365.4	-0.18	49.52
X-n459-k26	24181	24791	-2.52	16.43	25633	-6.00	103.9	24462.4	-1.16	60.59	24272.6	-0.38	42.80
X-n502-k39	69253	69966	-1.03	11.22	70190	-1.35	123.3	69346.8	-0.14	52.23	66898.0	3.40	71.94
X-n561-k42	42756	43587	-1.94	18.98	46905	-9.70	148.92	43131.3	-0.88	68.86	42866.4	-0.26	60.60
X-n613-k62	59778	61076	-2.17	16.25	66080	-10.54	160.14	60444.2	-1.11	74.8	59960.0	-0.30	117.31
X-n655-k131	106780	107397	-0.58	13.05	107336	-0.52	188.78	106782.0	0.00	47.24	106899.1	-0.11	150.48
X-n701-k44	82292	83348	-1.28	27.67	88696	-7.78	201.53	83042.2	-0.91	210.08	82487.4	-0.24	253.17
X-n766-k71	114683	117099	-2.11	24.98	125165	-9.14	247.97	115738	-0.92	242.11	115147.9	-0.41	382.99
X-n801-k40	73587	75252	-2.26	29.46	77487	-5.30	329.75	74005.7	-0.57	432.64	73731.0	-0.20	289.24
X-n856-k95	89060	90163	-1.24	27.85	91092	-2.28	384.07	89277.6	-0.24	153.65	89238.7	-0.20	288.43
X-n916-k207	329836	333432	-1.09	32.30	338116	-2.51	379.13	330948	-0.34	226.08	330198.3	-0.11	560.81
X-n957-k87	85672	86732	-1.24	40.91	88509	-3.31	459.63	85936.6	-0,31	311.2	85822.6	-0.18	432.9
X-n1001-k43	72742	74771	-2.79	39.39	81134	-11.54	482.75	73985.4	-1.71	792.75	72956.0	-0.29	549.03
Average	**71632.2**	**72680.80**	**-1.56**	**17.34**	**75105.60**	**-5.66**	**172.90**	**72012**	**-0.56**	**139.66**	**71649.00**	**-0.03**	**166.43**
				seconds			**seconds**			**minute**			**minute**

* Extracted average solutions, ILS-SP [29], UHGS [29], T1 is seconds, T2 is minutes

A9. Augerat et al. A Instances, KTA Initial and KTA with GA Solutions (Karagül-Tokat-Aydemir) [23, 24]

Instances		**KTA Initial**		**KTA with GA**			
P. Name	**BKS**	**Distance**	**Dev(%)**	**BestSol**	**Dev(%)**	**Time(sec)**	**Iteration**
A-n32-k5	784	1021.50	-30.29	804.04	-2.56	80.38	2
A-n33-k5	661	969.34	-45.65	662.26	-0.19	83.68	10
A-n33-k6	742	1021.60	-37.68	773.14	-4.20	94.64	8
A-n34-k5	778	1016.10	-30.60	807.77	-3.83	85.58	10
A-n36-k5	799	1032.80	-29.26	813.23	-1.78	90.63	5
A-n37-k5	669	942.26	-40.85	768.14	-14.82	92.88	9
A-n37-k6	949	1133.90	-19.48	960.68	-1.23	104.82	2
A-n38-k5	730	913.16	-25.09	740.74	-1.47	96.05	8
A-n39-k5	822	1212.30	-47.48	873.09	-6.21	98.66	2
A-n39-k6	831	1266.50	-52.41	903.91	-8.77	110.76	5
A-n44-k6	937	1295.80	-38.29	1011.68	-7.97	125.24	9
A-n45-k6	944	1300.10	-37.72	1008.96	-6.88	128.46	7
A-n45-k7	1146	1464.30	-27.77	1244.72	-8.61	142.65	3
A-n46-k7	914	1331.50	-45.68	994.35	-8.79	146.04	9
A-n48-k7	1073	1413.40	-31.72	1213.89	-13.13	152.34	6
A-n53-k7	1010	1596.00	-58.02	1061.15	-5.06	206.02	10
A-n54-k7	1167	1576.90	-35.12	1282.00	-9.85	209.32	10
A-n55-k9	1073	1587.20	-47.92	1093.95	-1.95	234.20	5
A-n60-k9	1354	1857.40	-37.18	1493.33	-10.29	265.41	10
A-n61-k9	1034	1438.70	-39.14	1122.83	-8.59	268.51	10
A-n62-k8	1288	1529.50	-18.75	1401.10	-8.78	251.95	7
A-n63-k9	1616	2259.10	-39.80	1738.33	-7.57	287.25	4
A-n63-k10	1314	1580.40	-20.27	1339.77	-1.96	288.30	5
A-n64-k9	1401	2024.00	-44.47	1527.84	-8.98	274.03	4
A-n65-k9	1174	1757.00	-49.66	1327.84	-12.82	287.85	10
A-n69-k9	1159	1738.90	-50.03	1345.47	-15.19	308.21	2
A-n80-k10	1763	2526.00	-43.28	1969.88	-11.67	387.23	2
Average	**1041.93**	**1437.25**	**-37.95**	**1121.63**	**-7.15**	**181.19**	**6.44**

A10. Augerat et al. B Instances, KTA Initial and KTA with GA Solutions(Karagül-Tokat-Aydemir) [23, 24]

Instances		KTA Initial		KTA with GA			
P. Name	**BKS**	**Distance**	**Dev(%)**	**BestSol**	**Dev(%)**	**Time(sec)**	**Iteration**
B-n31-k5	672	763.84	-13.67	699.30	-4.06	75.08	4
B-n34-k5	788	1022.70	-29.78	833.87	-5.82	82.90	10
B-n35-k5	955	1166.00	-22.09	965.97	-1.15	85.22	1
B-n38-k6	805	974.89	-21.10	825.68	-2.57	104.05	4
B-n39-k5	549	734.06	-33.71	581.64	-5.94	95.29	4
B-n41-k6	829	1006.00	-21.35	841.56	-1.52	112.98	8
B-n43-k6	742	854.68	-15.19	780.80	-1.19	119.09	9
B-n44-k7	909	1109.40	-22.05	975.26	-7.29	136.94	7
B-n45-k5	751	848.77	-13.02	773.19	-2.95	112.74	7
B-n45-k6	678	878.40	-29.56	680.47	-0.36	126.52	2
B-n50-k7	741	1065.10	-43.74	799.00	-7.83	157.03	3
B-n50-k8	1312	1617.70	-23.30	1346.18	-2.61	173.38	4
B-n51-k7	1032	1264.30	-22.51	1047.60	-1.51	161.04	5
B-n52-k7	747	1209.30	-61.89	769.00	-2.95	163.91	4
B-n56-k7	707	1063.90	-50.48	762.63	-7.87	178.11	6
B-n57-k7	1153	1672.00	-45.01	1177.64	-2.14	189.06	8
B-n57-k9	1598	1948.40	-21.93	1676.03	-4.88	249.59	5
B-n63-k10	1496	2048.30	-36.92	1643.03	-9.83	300.75	5
B-n64-k9	861	1201.60	-39.56	921.94	-7.08	279.54	7
B-n66-k9	1316	1710.70	-29.99	1380.55	-0.48	284.76	6
B-n67-k10	1032	1554.90	-50.67	1079.09	-4.56	318.17	9
B-n68-k9	1272	1714.70	-34.80	1341.92	-5.50	301.73	9
B-n78-k10	1221	1905.00	-56.02	1397.81	-10.41	340.87	1
Average	**963.74**	**1275.42**	**-32.10**	**1011.75**	**-4.37**	**180.38**	**5.56**

A11. Augerat et al. A Instances, KTA Initial and KTA with GA Solutions (Karagül-Tokat-Aydemir) [23, 24]

Instances		**KTA Initial**		**KTA with GA**			
P. Name	**BKS**	**Distance**	**Dev(%)**	**BestSol**	**Dev(%)**	**Time(sec)**	**Iteration**
P-n16-k8	450	461.32	-2.52	451.34	-0.30	41.30	3
P-n19-k2	212	262.77	-23.95	212.66	-0.31	22.94	7
P-n20-k2	216	266.29	-23.28	217.42	-0.66	24.66	7
P-n21-k2	211	261.41	-23.89	219.09	-3.84	25.39	3
P-n22-k2	216	262.21	-21.39	217.87	-0.87	26.60	7
P-n22-k8	603	693.09	-14.94	595.81	Oca.19	58.96	6
P-n23-k8	529	579.62	-9.57	531.17	-0.41	61.66	1
P-n40-k5	458	525.80	-14.80	475.31	-3.78	79.63	3
P-n45-k5	510	688.95	-35.09	542.11	-6.30	91.80	5
P-n50-k7	554	813.93	-46.92	593.19	-7.07	129.46	10
P-n50-k8	631	814.03	-29.01	659.51	-4.52	141.89	9
P-n50-k10	696	958.15	-37.67	708.85	-1.85	168.79	8
P-n51-k10	741	961.51	-29.76	767.41	-3.56	169.65	4
P-n55-k7	568	850.60	-49.75	629.45	-10.82	140.85	3
P-n55-k8	588	805.67	-37.02	619.62	-5.38	140.47	4
P-n55-k10	694	865.45	-24.70	729.68	-5.14	181.95	2
P-n55-k15	989	1262.80	-27.68	985.64	0.34	256.56	3
P-n60-k10	744	1015.20	-36.45	820.50	-10.28	203.52	2
P-n60-k15	968	1231.00	-27.17	1032.95	-6.71	360.50	8
P-n65-k10	792	1140.90	44.05	864.26	-9.12	280.13	10
P-n70-k10	827	1019.20	-23.24	905.41	-9.48	306.09	8
P-n74-k4	593	952.07	-60.55	711.61	-20.00	181.50	2
P-n76-k5	627	929.96	-48.32	752.04	-19.94	204.16	6
P-n101-k4	681	1110.40	-63.05	837.99	-23.05	261.78	7
Average	**587.42**	**780.51**	**-31.45**	**628.37**	**-6.33**	**148.34**	**5.33**