Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management
Bali, Indonesia, January 7 – 9, 2014

Application of Memetic Algorithm to Solve Truck and Trailer Routing Problems

Seyedmehdi Mirmohammadsadeghi
Department of Mechanical Engineering
University of Malaya
50603 Kuala Lumpur, Malaysia

Shamsuddin Ahmed
Department of Mechanical Engineering
University of Malaya
50603 Kuala Lumpur, Malaysia

Eida Nadirah binti Roslin
Department of Mechanical Engineering
University of Malaya
50603 Kuala Lumpur, Malaysia

Abstract

Application of memetic algorithm (MA) is considered in this work to solve the truck and trailer routing problem (TTRP). In TTRP, some customers can be designated as vehicle customers and can be serviced either by a complete vehicle (a trailer pulling by truck) or a single truck. However, some customers are known as truck customers and have to be serviced by a single truck. To employ this algorithm, Partial-mapped crossover (PMX), various mutations and local search approaches have been applied and a truck and trailer routing problem has been solved. The results compared with the findings available in the literature. The MA used for this purpose obtained 13 best solutions out of 21, including 10 new solutions. The results obtained from the application of MA are better than other algorithms such as tabu search and simulated annealing. Therefore, application of MA is useful for solving TTRP.

Keywords
Truck and trailer routing problem, vehicle routing problem, memetic algorithm, heuristics

1. Introduction

Truck and trailer routing problems (TTRP) are related to transporting manufacturing goods within a plant or factory floors or delivering products to markets or customers. TTRP is a variant of the vehicle routing problem (VRP). Indeed, VRP has been known as one of the most studied combinatorial optimization problem in the past few decades since it covered certain areas in practice and considered complexities to a reasonable extent (Golden and Assad, 1988, Laporte et al., 2000). VRP concept has been extended since 1959. In 1959, Ramser and Dantzing introduced this terminology (Dantzig and Ramser, 1959). They defined it as a generalized solution on Travelling Salesman Problem (TSP). After that many researchers have extended this concept to make it useful in diverse areas. During the last two decades, some constraints were added to the VRP such as time window, travel and service time. However, because of some obstacles which come out in real life time, such as government regulations, limited space to maneuver at customer site and road conditions, maneuvering a complete vehicle (truck pulling a trailer) is very difficult and only a truck may serve some of the customers. These constraints can be found in many practical situations (Lin et al., 2009). Consequently, as VRP cannot consider these issues. They should be considered in TTRP model.

In the TTRP, sometimes trucks pull a trailer to serve the customers that is when the usage of trailers is considered (which is a feature that usually is ignored in the VRP). Some researchers have been working in this field. Gerdessen worked on The Vehicle Routing Problem with trailer (Gerdessen, 1996). He demonstrated two actual applications which are relevant to TTRP. The first one is the distribution of dairy products in which many customers were located in cities where heavy traffic is the reality. Because maneuvering a complete vehicle was so difficult in this area, therefore the trailer often parked in parking places and the truck serviced customers. The second application is to distribute component animal feed to farmers. Because most of villages have narrow roads or small bridges, different kinds of vehicles are required to deliver the feed to farmers. One kind of vehicles is called double bottom. It consists of a truck and a trailer. While the truck is making sub-tours (some parts of tour) the trailer parks at parking area. Another application which is relevant to TTRP is introduced by Semet and Taillard (Semet and Taillard, 1993). The application occurred in a major chain food market with 45 groceries. They located in Swiss state. The markets were serviced by a fleet of 21 trucks and 7 trailers. This scheduling for servicing customers with a combinational truck and trailer is interested for researchers.

TTRP model was first proposed by Chao (Chao, 2002). Then Scheuerer applied an 0-1 integer programming formulation for solving TTRP. TTRP was formulated in integer programming by Scheuerer for the first time in 2006 (Scheuerer, 2006). Chao (Chao, 2002) and Scheuerer (Scheuerer, 2006) used a 2-phase approach for solving TTRP. They used heuristics to construct the initial TTRP solution in the first phase. In the second phase, they used Tabu search algorithm to improve the initial solution. Chao followed Fisher and Jaikumar's construction for vehicle routing (Fisher and Jaikumar, 1981). Scheuerer (Scheuerer, 2006) used Chao's model and improve it by using two construction heuristics, T-Cluster and T-Sweep, applied new tabu search improvement algorithm for the TTRP. Lin et al (Lin et al., 2009) introduced simulated annealing to solve TTRP and obtained 17 best solutions to the 21 TTRP benchmark (Lin et al., 2009). Then they applied time windows constraint in TTRP solution for the first time to bring the model closer to the reality (Lin et al., 2011).

When making comparison between VRP and TTRP, TTRP is computationally much more difficult to solve. Hence TTRP is more general and VRP is a special case of TTRP. Therefore, TTRP can be reduced to VRP if vehicles are the same without any trailer. In addition, VRP is one of the most difficult combinatorial optimization problems. It should be tackled by heuristics approaches (Chin et al., 1999, Laporte et al., 2000, Cordone and Calvo, 2001, Baker and Ayechew, 2003, Eksioglu et al., 2009).

In this study, memetic algorithm is applied to justify its appropriateness in solving TTRP along with other meta-heuristics algorithms particularly, tabu search (TS) and simulated annealing (SA). The computational results demonstrate that the performance of MA is better than TS and SA since it can produce 10 new solutions out of 21 benchmark TTRP instances.

2. Memetic algorithm for TTRP

TTRP is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \dots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by 'v_0' and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a deterministic and non-negative demand q_i to be collected. They are not splittable at the vertex. A customer type t_i is available for all customers. Also $t_i = 1$ shows that customer i is truck customer (TC) and can be serviced only by single truck. If $t_i = 0$, a customer i is a vehicle customer (VC) and it can be serviced by single truck or complete vehicle (truck pulling a trailer). $C = (c(v_i, v_j))$ is a symmetric travel cost which is defined on E. It is assumed that all vehicles are the same and have the same speed, so the travel cost is equal to Euclidean distance between v_i and v_j.

Say, a fleet of m_k and m_r number of truck and trailer are available, respectively. Without loss of generality, it is assumed that $m_k \geq m_r$, as in Chao (Chao, 2002) and Scheuerer (Scheuerer, 2006) and Lin et al (Lin et al., 2009, Lin et al., 2010, Lin et al., 2011). All trucks have the same capacity Q_k, and all trailers have the same capacity Q_r, where Q_k and Q_r are different.

Three types of route are available in TTRP as follow: 1) a pure travel route (PTR). It can be traveled by only single truck. 2) A pure vehicle route without any sub-tour (PVR). Only complete vehicle can be traveled in this route. 3) Complete vehicle route (CVR). It consists of a main tour and at least one sub-tour (ST). A sub-tour starts and finished at the same vehicle customer (v_r) (trailer is parked in parking place which is called root) and it can be traveled only by single truck; however, it should be serviced by complete vehicle in main tour.

Memetic Algorithms (MAs) fit into the category of the evolutionary algorithms (EAs) where local search procedures are used to distribute the search area and enhance the search to refine individuals. Actually, MA is a hybrid algorithm which combine the population and local search procedures to improve the initial solutions. The inspiration for MA was realized from the adaptation models in the natural systems. These models combine the lifetime learning of an individual with the populations' evolutionary adaptation (Tavakkoli-Moghaddam et al., 2006). Besides, another inspiration of the MAs was obtained from the concept of meme from Dawkin. A cultural evolution unit is represented by this concept and it can indicate the local refinement (Tavakkoli-Moghaddam et al., 2006) and can be applied for solving TTRP.

In applied MA, the population P consists of a set of individuals which are generated randomly. Each individual is called a 'chromosome', which is simply a permutation of the set of n nodes (customers) $\{1,2,\dots,n\}$ and N dummy zeros (artificial store or the root of sub-tour). This idea was initially proposed by Beasley (1983) as part of a route-first cluster-second heuristic, and was then used by Prins (2004). Recently, this method was applied to other versions of the VRP, such as heterogeneous fleets (Prins, 2009), pickup and delivery vehicle routing problem (Velasco et al., 2009) and TTRP (Villegas et al., 2010).

The presentation of the solution for TTRP is explained more as follows. In each stage, offsprings are randomly generated from the initial population. Firstly, two chromosomes (parents) are randomly selected and two new chromosomes (offsprings) are produced by crossover operation. The functional value is computed by the chromosomes. The new solutions are compared with the existing solutions. If a new solution is better than an existing solution, the algorithm replaces the existing solution with the new one. Then the new solution can be improved by mutations and local search procedures. This procedure is continued until the termination condition occurred.

2.1 Initial population

Generally, evolutionary algorithms generate the initial population at random. This initial population helps the algorithm to be representative from any area of search space. In this paper, a particular method is used to produce the initial population as follows.

All customers are classified as truck customers (TCs) and vehicle customers (VCs). A string of numbers represents an initial solution, which is denoted by the set $\{1,2,\dots,n\}$ and N dummy zeros (see Figure 1). The parameter N is utilized to terminate sub-tour or route and can be calculated by $\lfloor \sum_i q_i / (Q_k) \rfloor$ where $\lfloor \bullet \rfloor$ denotes the largest integer which is equal or smaller than to the enclosed number. The *i*th non-zero number in the first $n + N$ positions denotes the *i*th customer to be serviced. Vehicle customer can be serviced either by complete vehicle or a single truck and the service vehicle type can be of 1 or 0. Therefore, the vehicle type of VC is 1 if it is serviced by a single truck. Otherwise its vehicle type is 0 and must be serviced by a complete vehicle. Hence TC must be serviced only by truck vehicle, therefore does not need to be mentioned in the solution (Lin et al., 2009).

The presentation of the initial population is explained more as follows. In this solution, the first number addresses the first customer that is to be served on the first route. A PTR is decided for the route, if a single truck is to service the first customer on a route. To represent the servicing sequence, from left to right, one by one, other customers are added to the route. Note that if it is a complete vehicle on the CVR main tour or on a PVR, the vehicle capacity may be $(Q_k + Q_r)$ or on a CVR sub-tour or on a PTR, if it is a single truck, which is servicing the customers alone, it may be Q_r and it all depends on the type of the vehicle, which is in use of a service. If in the representation of the solution, the next customer, which is to be served, is zero, the vehicle will return to the depot or the root of a sub-tour. If it is on a CVR sub-tour, the sub-tour will be terminated, because the vehicle returns to the root of the sub-tour. If not, it is on a CVR main tour, on a PVR or on a PTR. In this case, the vehicle goes back to the depot and the route is terminated. In the solution representation, generation of a new route will be occurred, if the termination of previous route has been taken place and there are still have customers yet to be serviced. Therefore, the next customer will be selected for new route. Figure 2 illustrates a simple individual representation in MA. Customer 3 and 2 are supposed to be TC and must be serviced in sub-tour by a single truck and other customers are supposed to be VC and can be serviced by either single truck or complete vehicle. At first, customers 4, 5, 7, 6 are serviced by complete vehicle. Therefore, customer 6 is the parking place (root) and the trailer has to be parked at this area during servicing customers 3 and 2. Finally, the customer 1 is serviced and the route is finished by returning the complete vehicle into depot. A TTRP solution is given by this solution representation, without violating from the constraints and it can be verified. On the other hand, by using this solution representation, the number of the vehicles that are used might exceed the available vehicles. As a result, after the solution representation has generated the routes, in order to decrease the number of the vehicles that are used in a procedure for route combination is considered necessary. The procedure of the route combination checks the possibility of combining any two existing routes. However, this combination process must not violate the constraint of the capacity of the vehicle and if there are routes that can be combined together without the violation of this constraint they will be merged without any modification. This process goes on until the number of the used vehicles is not greater than the number of the vehicles available or it will stop if there are not any more routes that can be combined together without violating the assumptions. If the outcome solution still persists on using more vehicles than there are available, for each additional trailer or truck that is used, a cost of *P*, as a penalty, is added to the objective function in order to make the solutions of this type undesirable (Lin et al., 2009).

4	7	2	12	5	16	10	17	0	8	1	14	15	11	13	0	3	19	20	9	18	6	0
Route 1 CVR									Route 2 PTR							Route 3 PVR						

Figure 1: A sample TTRP representation with 20 customers and 3 dummy zeros

4	5	7	6	3	2	1

Figure **2**: Representation of an individual **(**chromosome**)** in MA

2.2 Crossover operator

Partial-mapped crossover (PMX) has been considered to the permutation representation. PMX was first proposed by Goldberg and Lingle (Goldberg and Robert Lingle, 1985). PMX operator is an extension of two-point crossover. Two-point crossover is used for a binary string, and some infeasible solutions may occur by using this operator. However, PMX uses some procedures to fix this illegitimacy (infeasible solutions) by repairing solutions caused by two-point crossover. Firstly, two positions in the chromosome are randomly selected and the sub-chromosomes are situated between these positions are substituted. Then the relations between two mapping sections are determined. Finally, the remained notes are arranged according to discover relations. This PMX operator is considered for TTRP. The sample representation of a PMX is depicted in Figure 3. In this figure, two samples parent chromosomes are selected and two new offsprings are produced according to PMX. Firstly, shadow customers (sub-chromosomes) are selected. Then all customers in this sub-chromosome are replaced and finally remained customers are allocated according to find relations.

Parent 1	2	6	4	7	11	17	15	3	8	9	12
Parent 2	3	9	4	8	6	2	15	12	7	11	17
Offspring 1	7	4	17	8	6	2	15	12	3	9	11
Offspring 2	12	6	8	7	11	17	15	3	9	4	2

Figure 3: Partial-mapped crossover for TTRP

2.3 Mutation operators

In this work, different types of mutations such as displacement, inversion and change of service vehicle type of vehicle customers (VCs) have been used to improve the solutions. The displacement mutation is implemented by selecting the sub-tour randomly and inserting it in a new random situation. The inversion mutation is carried out by selecting two customers in the chromosome and reverses the route from larger numbers to smaller ones. The change of service vehicle type of VCs from 1 to 0 or 0 to 1 is fulfilled by selecting a vehicle customer randomly. If it is serviced by a single truck (1) in the current solution, its service vehicle type will be changed to a complete vehicle (0) and vice versa. It means that the service vehicle type of a selected VC will be changed from 1 to 0 or 0 to 1. For example, VC customer is serviced in the main-tour by a complete vehicle will be serviced on a sub-tour by a single truck and vice versa. Figure 4 and 5 illustrate different types of mutations which are used in MA to improve the initial solutions. In these figures, a sample parent chromosome is selected and a new offspring is produced according to displacement and inversion mutations. In figure 4, shadow sub-chromosome is randomly selected for displacement mutation. Then bolded positions are randomly selected. Finally, the offspring is produced by moving the shadow sub-chromosome to the bolded positions and the other nodes are arranged according to discover relations with shadow sub-chromosome. In figure 5, customers 3 and 4 are randomly selected for inversion mutation. Then the route is reversed from customer 3 to customer 4 in corresponded positions between these customers.

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	**17**	**15**	**3**	4	7	11	8	9	12

Figure 4: Displacement mutation for TTRP

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	3	15	17	11	7	4	8	9	12

Figure 5: Inversion mutation for TTRP

2.4 Local search

After applying crossover and mutations procedures, the local search (LS) approach is applied for improving the initial solutions of TTRP (chromosomes) in the pool of customers' candidates. Four different local search procedures were used in this work are as follows. 1- One-point movement procedure 2- Two-point exchange procedure 3- Change of sub-tour root procedure 4- 2-Opt procedure.

In the one-point movement step (OPM), the customer is moved from a route to another route. Also one customer is considered at the time. In executing the movement, two candidate passes must be excluded: (1) move a TC customer to the main-tours of the CVR or two PVR and (2) To move a VC customer that the parking-location of the sub-tour (this is known as the root node). Firstly, the algorithm examines customers on the PTR and the main tours, and then the sub tour customers should be examined.

In a two-point exchange stage (TPE), two customers of two different routes should be replaced. Moving a TC customer into the main tour in the CVR or into a PVR, or move the root node of the sub-tour is banned. When customers switched between two routes, all of the sub-route continues to be feasible considering truck capacity.

In the previous two steps, the root node never changes its position. It may be improving the solution while some of the root nodes are replaced. In this stage, re-selecting roots or re-sequencing the customers are considered.

The 2-Opt procedure deletes two edges of the route and the rest of the segments are to reconnect in any other possible situations. If portable reconnected is found (i.e. the first or best), then it is applied. The process repeats until no further improvements can be achieved and therefore the local optimum route was obtained.

3. Application of MA and other methods

The algorithm proposed above was coded using MATLAB 7.9.0 and has run on a laptop with 2.4 GHz dual processor and 4 G RAM.

For solving TTRP, 21 TTRP benchmark problems which were generated by Chao (Chao, 2002) have been considered. This benchmark is derived from Christofides et al., (Christofides et al., 1979). To evaluate the performance of the solutions, the results are compared with Chao (Chao, 2002), Scheuerer (Scheuerer, 2006) and Lin et al., (Lin et al., 2010). Chao and Scheuerer used proposed tabu search while Lin et al., used proposed SA for solving TTRP. The results from Chao, Scheuerer, Lin et al., and proposed MA are presented in Table 2. Each instance has been run in 10 times and the best solutions from 10 run are located in the last column. Also the time taken for best solutions is presented in the next columns. In addition, Table 1 shows the number of customers and the capacity of each truck and trailer which are mentioned by Chao (Chao, 2002).

Table 1: Dimensions of the TTRP benchmark problems proposed by Chao (Chao, 2002)

Problem ID	Number of VC	Number of TC	Truck capacity	Trailer capacity	Ratio of demand to capacity
1	38	12	100	100	0.971
2	25	25	100	100	0.971
3	13	37	100	100	0.971
4	57	18	100	100	0.974
5	38	37	100	100	0.974
6	19	56	100	100	0.974
7	75	25	100	100	0.911
8	50	50	100	100	0.911
9	25	75	100	100	0.911
10	113	37	100	100	0.931
11	150	75	100	100	0.931
12	100	112	100	100	0.931
13	150	49	150	150	0.923
14	100	99	150	150	0.923
15	50	149	150	150	0.923
16	90	20	150	150	0.948
17	60	60	150	150	0.948
18	30	90	150	150	0.948
19	75	25	150	150	0.903
20	50	50	150	150	0.903
21	25	75	150	150	0.903

Table 2: Results obtained using MA and other approaches

ID	Chao	Time	Scheuerer	Time	Lin	Time	Proposed MA	Time	Best solution
1	565.02	4.19	566.80	9.51	557.11	6.77	**553.62**	5.44	553.62
2	662.84	5.22	615.66	9.60	608.22	6.66	610.21	6.57	608.22
3	664.73	6.50	620.78	11.24	618.04	5.35	**618.04**	6.84	618.04
4	857.84	7.53	801.60	18.49	784.73	15.53	785.83	13.91	784.73
5	949.98	7.06	839.62	15.16	839.62	14.73	**839.62**	13.09	839.62
6	1084.82	7.96	936.01	18.62	930.64	12.58	**928.92**	11.78	928.92
7	837.80	16.43	830.48	33.60	810.38	24.63	812.09	22.87	810.38
8	906.16	11.11	878.87	25.66	873.80	24.29	**871.65**	22.94	871.65
9	1000.27	10.18	942.31	30.47	911.49	21.27	**909.60**	23.45	909.60
10	1076.88	21.72	1039.23	60.94	1018.62	63.55	1022.49	55.43	1018.62
11	1170.17	17.10	1098.84	56.17	1076.88	60.10	**1073.89**	57.33	1073.89
12	1217.01	20.27	1175.23	63.71	1154.13	51.22	1160.43	48.27	1154.13
13	1364.50	42.34	1288.46	165.41	1263.62	119.51	**1262.22**	102.58	1262.22
14	1464.20	25.96	1371.42	132.06	1336.03	112.66	**1332.99**	105.06	1332.99
15	1544.21	24.62	1459.55	154.10	1422.22	92.27	**1411.82**	88.00	1411.82
16	1064.89	14.56	1002.49	43.14	975.65	40.64	983.93	42.11	975.65
17	1104.67	13.74	1042.35	33.73	1006.79	37.55	**1001.12**	34.56	1001.12
18	1202.00	12.52	1129.16	31.78	1097.56	31.09	**1096.10**	28.21	1096.10
19	887.22	16.13	813.50	28.84	797.19	29.18	801.72	31.29	797.19
20	963.06	10.09	848.93	24.57	847.21	29.00	**847.21**	27.73	847.21
21	952.29	9.57	909.06	24.57	909.06	23.94	910.41	21.53	909.06
Average	1025.74	14.51	962.40	47.32	944.71	38.18	944.47	36.62	943.08

The solutions obtained by proposed MA and other approaches are compare in Table 2. Table 2 indicates that the proposed MA obtained 13 best solutions from 21 which are bolded in this table. The average solution is 944.47 which is slightly better than Lin's average solution (944.71). However, the average results from Chao and Scheuerer are 1025.74 and 962.40, respectively. So, the differences between results obtained by MA and tabu search are considerable. Also the time taken is mentioned in Table 2. It can be seen that the average time taken to be produced for memetic algorithm is 36.62 minutes. Thus, the problems are solved in shorter time in compared with other algorithm. Table 3 compared the results obtained from proposed MA with other approaches

Table 3: Comparison of MA with other approaches

Problem ID	Comparison of best solution between proposed MA and Chao's results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and Scheuerer's results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and Lin's results (MA-SA)/SA (%)
1	−2.00	−2.30	−0.60
2	−7.90	−0.90	0.30
3	−7.00	−0.50	0.00
4	−9.00	−2.00	0.10
5	−11.6	0.00	0.00
6	−14.3	−0.80	−0.20
7	−3.00	−2.20	0.20
8	−3.80	−0.80	−0.30
9	−9.00	−3.40	−0.20
10	−5.00	−1.60	0.30
11	−8.20	−2.30	−0.30
12	−4.70	−1.30	0.50
13	−7.50	−2.00	−0.10
14	−9.00	−2.80	−0.20
15	−8.60	−3.20	−0.70
16	−7.60	−1.80	0.90
17	−9.30	−3.90	−0.50
18	−8.80	−3.00	−0.10
19	−9.60	−1.50	0.50
20	−12.0	−0.20	0.00
21	−4.40	0.10	0.10
Average	−7.73	−1.73	−0.014

Table 3 indicates that the average results obtained by proposed MA have been improved about 7.73 percent, 1.73 percent and 0.014 percent compared with Chao's results, Scheuerer' results and Lin's results, respectively. In addition, average computing time for solving the problems by MA is less than others. Consequently, the performance of proposed MA is slightly better than SA and TS and the results can be accepted as the new solutions.

4. Conclusion

In this paper, the proposed MA has been used to solve TTRP. The results have been compared with existing approaches. The memetic algorithm has been applied to solve this problem. Partial-mapped crossover (PMX) and different kinds of mutations such as inversion, displacement and change of service vehicle type of VCs are applied for this algorithm. In addition, various types of local search approaches are used for improving the chromosome in the pool of candidates to find better solutions. The results have been compared with previous findings obtained by other researchers to show the validity of the solutions and the results indicate that the proposed MA is efficient and effective for solving TTRP. The proposed MA obtained 13 best solutions from 21 including 10 new best solutions and 3 best solutions which are previously reported by other approaches. Future research may attempt to extend the TTRP by introducing more practical or real-world conditions such as time windows and multi depot. Also work on

TTRP with stochastic parameters to solve the real-life problems in the manufacturing and transportation systems can be considered. Consequently, TTRP benchmark instance problems from Chao's benchmarks need to be modified for this purpose.

Acknowledgement

This paper acknowledges the financial support from the University of Malaya Research Grant, UMRG Project RG139/12AET for this research.

References

Baker, B. M. & Ayechew, M. A. A genetic algorithm for the vehicle routing problem. *Computers & Operations Research,* 30**,** 787-800, 2003

Chao, I. M.. A tabu search method for the truck and trailer routing problem. *Computers & Operations Research,* 29**,** 33-51, 2002.

Chin, A. J., Kit, H. W. & Lim, A. A New GA Approach for the Vehicle Routing Problem. *Proceedings of the 11th IEEE International Conference on Tools with Artificial Intelligence.* IEEE Computer Society, 1999.

Christofides, N., Mingozzi, A. & Toth, P. The vehicle routing problem. *Combinatorial optimization,* 11**,** 315-338, 1979.

Cordone, R. & Calvo, R. W. A heuristic for the vehicle routing problem with time windows. *Journal of Heuristics,* 7**,** 107-129, 2001.

Dantzig, G. B. & Ramser, J. H. The Truck Dispatching Problem. *Management Science,* 6**,** 80-91, 1959.

Eksioglu, B., Vural, A. V. & Reisman, A. The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering,* 57**,** 1472-1483, 2009.

Fisher, M. L. & Jaikumar, R. A generalized assignment heuristic for vehicle routing. *Networks,* 11**,** 109-124, 1981.

Gerdessen, J. C. Vehicle routing problem with trailers. *European Journal of Operational Research,* 93**,** 135-147, 1996.

Goldberg, D. E. & Robert Lingle, J. AllelesLoci and the Traveling Salesman Problem. *Proceedings of the 1st International Conference on Genetic Algorithms.* L. Erlbaum Associates Inc, 1985.

Golden, B. L. & Assad, A. *Vehicle Routing: Methods and Studies,* North-Holland, 1988.

Laporte, G., Gendreau, M., Potvin, J.-Y. & Semet, F. Classical and modern heuristics for the vehicle routing problem. *International Transactions in Operational Research,* 7**,** 285-300, 2000.

Lin, S.-W., Yu, V. F. & Chou, S.-Y. Solving the truck and trailer routing problem based on a simulated annealing heuristic. *Computers & Operations Research,* 36**,** 1683-1692, 2009.

Lin, S.-W., Yu, V. F. & Chou, S.-Y. A note on the truck and trailer routing problem. *Expert Systems with Applications,* 37**,** 899-903, 2010.

Lin, S.-W., Yu, V. F. & Lu, C.-C. A simulated annealing heuristic for the truck and trailer routing problem with time windows. *Expert Systems with Applications,* 38**,** 15244-15252, 2011.

Scheuerer, S. A tabu search heuristic for the truck and trailer routing problem. *Computers & Operations Research,* 33**,** 894-909, 2006.

Semet, F. A two-phase algorithm for the partial accessibility constrained vehicle routing problem. *Annals of Operations Research,* 61**,** 45-65, 1995.

Tavakkoli-Moghaddam, R., Saremi, A. R. & Ziaee, M. S. A memetic algorithm for a vehicle routing problem with backhauls. *Applied Mathematics and Computation,* 181**,** 1049-1060, 2006.

Biography

Seyedmehdi Mirmohammadsadeghi is currently a PhD Candidate in the Department of Mechanical Engineering at Faculty of Engineering, University of Malaya. He obtained his first degree in Industrial Engineering from University of Yazd, Iran. He did his Master of Engineering degree from Khajeh Nassir Toosi University of Technology, Iran. He submitted 5 papers in ISI-indexed journals and conferences. His research interests are in areas of operations research, supply chain management, quality & reliability engineering, and maintenance engineering. He has been working at University of Malaya from 2011 as a research assistant.

Shamsuddin Ahmed Muhammad Shahadat Ullah is currently an Assoc. Professor in the Department of Mechanical Engineering at Faculty of Engineering, University of Malaya. In University of Malaya, other than designing/introducing and teaching a good number of subjects for both undergraduate and postgraduate classes, he supervised to graduate seven (7) PhD, and more than one dozen MEngSc and MEng candidates. To his credit, he published about 75 journal papers and 105 conference articles. About 35 of his papers were published in ISI-indexed journals and conferences. His overall h-index is 12 (i10-index is 18) and ISI h-idex is 5. Total ISI citation is 87 and the overall citation is about 672. His research ID link is http://www.researcherid.com/rid/B-9740-2010, and Scopus ID link is http://scholar.google.com/citations?. His research interests are in areas of manufacturing planning & control, manufacturing energy savings, supply chain management, operations research, quality & reliability engineering, and maintenance engineering. Currently 5 PhD and several masters' students are working under his supervision.

Eida Nadirah Roslin is currently a PhD Candidate in the Department of Mechanical Engineering at Faculty of Engineering, University of Malaya. She obtained her Bach. Engineering from International Islamic University Malaysia and Master of Engineering in Manufacturing System from Universiti Putra Malaysia. She was an Engineer at Production Engineering Department, PROTON Berhad and a Project Engineer at TNB Engineering Corporation Sdn Bhd. Her research interests include manufacturing system, operation management and Lean.