Journal of Applied Business and Finance Researches

Volume 3, Issue 2: 55-65 (2014)

JABFR JOURNAL OF APPLIED BUSINESS AND FINANCE RESEARCHES

Designing Routes of Various Depot Multiple Traveling Salesman Problem by Using of Genetic Algorithm

Ebrahim Abbasi, [1], Meisam Garakani, [2*], Mehdi Abvali[2]

[1]*Associate Professor of Financial Management, Alzahra University, Garmsar, Semnan, Iran*
[2]*Lecturer of University, Eyvanakey Institute of Higher Education, Garmsar, Semnan, Iran*

*Corresponding author's Email: meisam.garakani@Yahoo.com

ORIGINAL ARTICLE
Received 29 Sep. 2013
Accepted 22 Dec. 2013

ABSTRACT: The various depots multiple traveling salesman (VmTSP) is the normal status of multiple traveling salesman problem (mTSP) whereas there is more than one depot and multiple salesmen in each depot. The functional purpose of this problem includes minimizing all travels for each salesman as each salesman starts its own travel from one specific depot and returns to the same depot. Since this problem is related to NP-Hard, it is impossible to solve it in this real world. Thus; we used some Meta heuristic methods in order to achieve some approximate efficient results. We used Meta Heuristic standard genetic algorithm to solve this problem. Despite comparing the final results of limited problem with efficient result, the efficiency of parameters as well as the strategy of choosing are compared in large scaled in this Meta Heuristic method. In addition, the suggestive parameters (New-MX cross-over parameter) in genetic algorithm in an extremely large sizes (100 cities), large (150 cities), and extra large scale (200 cities) are compared separately, the results show the better combinations of UX#2 cross-over parameter and the selection strategy of elite parents in extra large scale, the combination of suggestive New-MX cross-over parameter, and the competitive binary strategy in large scale as well as the combination of PMX cross-over parameter with the binary selection strategy in an extremely large scale.

Key words: VmTSP, Meta Heuristic, Genetic Algorithm
JEL Classification: C_{44}, C_{61}, M_{54}

INTRODUCTION

Today by the development of manufacturing industry, strong global competition among companies and corporations, the transient life cycle of goods, the necessary time for marketing as well as various needs of customers in different places with different distances from manufacturing place made some corporations in goods and raw material delivery or transiting companies promote their efficiency. These transiting and delivery systems must be able to deliver goods with the least cost in the least possible time to submit them to the customers on time. One more general form of the famous traveling salesman problem (TSP) is the multiple traveling salesman problem (mTSP) that consists of finding a collection of travels form salesmen who start from one specific depot and return to it. In addition, the various depots multiple traveling salesman problem (VmTSP) is the general form of single depot multiple traveling salesmen problem whereas despite multi depots, there should be multiple salesmen in each depot. The required problem of this research is determining some specific numbers of travels for each traveling salesman as that salesman is obliged to return to the depot where they stated their travel. This problem is known as fixed depot traveling salesman problem.

Literature Review

Of the first heuristic methods for solving *m* travel in TSP was introduced by Russel (Kara, 2006) with some limitations. Although the method of solving was based on converting the problem to simple TSP and developing it on a graph, its algorithm was the expanded model of heuristic method which was given earlier by Lin and Kernighan (Lin, 1973) for TSP.

The other heuristic method based on the exchange procedure for mTSP was introduced by Potvin et al (Carlos et al, 2013). The Parallelism Processing Approach for solving mTSP by the use of evolutionary programming was first framed by Fogel (Fogel, 2008). There are two salesmen with one purpose traveling this approach that minimizes the variance between the undertaken travels for each salesman. Some problems by the limitation of 25 or 50 cities were solved by this improving method which showed some suitable responses approximate to optimum. Wachodler et al. (1989) expanded Hopfield-Tank ANN model for mTSP. But this model is considered complex due to the disability to guaranty the feasible solutions (Somhom, 1999). Hsu et al. (1991) offered one Neural networks Approach for solving mTSP based on solving *m* problems of standard TSP. These writers pointed out that they achieved better results comparing with what Wachodler et al. mentioned. One self-organized approach to neural networks for mTSP is related to Wakhotinsky and Golden (1994) which was offered based on Elastic Net approach for TSP problem. Recently, Modares et al. (1999) was well as Somhom et al. (1999) introduced one self-organized NN approach for mTSP with one minimizing purpose travel that minimizes the cost of the most expensive travel among salesmen.

Using genetic algorithm (GA) for solving mTSP was first offered by Zhang et al. (2006). One recent uses of this is related to Tang et al. (2000) who used genetic Algorithm for solving the expanded model of mTSP to program hot rolling Scheduling. The solving is as follow: first, this problem is modeled in the form of mTSP. Then; this problem is converted to a simple TSP. Finally, one refined genetic algorithm is applied on it to find the respond. Yu et al. (2002) also used genetic algorithm for solving mTSP in designing the travels. Taboo search algorithm (TS) for mTSP was used by Ryan et al. (2011) by an open timing. These writers offered one Integer numerical programming formulation which was solved by TS algorithm in the format of discreet event stimulation.

Recently, Song et al. (2003) suggested simulated Annealing Approach for mTSP with fixed costs for salesmen. This approach was applied for mTSP for 400 cities and 3 salesmen that responded in a suitable time table. Gomes and Von Zuben (2009) offered one method based on Neuro-Fuzzy system for solving mTSP used in capacitated VRP which is a network approach based on Fuzzy limitations. Sofge et al. (2002) performed and compared some developed algorithm for solving mTSP that consisted of neighborhood attractor schema, Shrink-Wrap algorithm for Local neighborhood Optimization, particle Swarm optimization, Monte-Carlo Optimization, Genetic Algorithm, and other developing strategies. Table 1 illustrated various solving methods of mTSP:

Table 1- mTSP Solutions

Problem approach	**Solving methods**
Exact solution methods	Linear programming formulas [4], [5] Cutting planes [6] Branch and bound [8], [28] Lagrange's method with branch and bound [7]
Heuristic methods	Simple Heuristic methods [9], [11] Evolutional algorithms [12] Simulated Annealing (SA) [19] Taboo search (TA) [3] * Genetic algorithms (GA) [1], [2], [18] Neural networks (NN) [13], [14], [15], [16], [17]
Converts	Asymmetric mTSP to asymmetric TSP [22] Symmetric mTSP to symmetric TSP [23], [24], [25] VmTSP to TSP [26], [27]

Problem Solving

Some parameters are used in solving the problem defined as follow:

Decision variable: This model is based on the 3-indicators x_{ijk} decision variable as follow

$$x_{ijk} = \begin{cases} 1 & \text{If a salesman who exits from k depot crosses (i,j) arc} \\ 0 & \text{Otherwise} \end{cases}$$

This variable considers 1 foe those crossed arc in the travels, and 0 for other arcs. In fact, considering this binary variable, those arcs from which no salesman is crossed are deleted for the response. we can reach the result by concluding other variable arcs in the response .since each salesman should return to the depot where he exists, the third indicator k is considered for depicting the dependence if each arc to one depot in this decision variable.

Input parameters:

c_{ij}: Distance between i and j cities
N: the number of total locations
M: The number of salesmen
d: the number of depots
M_k: the number of salesmen in k depot
V: The total locations (cities)
V': The total intermediate locations (intermediated cities)
D: Total depots
L: the maximum number if intermediate cities for each salesman to visit
K: the minimum number of intermediate cities for each salesman to visit
u_i: The total visited cities for each salesman before arriving to i city (including depot)

Statement of the problem

Consider the complete directed graph $G=(V,A)$ in which V is the total n points (vertices), A is the total arcs, and $C=(c_{ij})$ is the cost matrix (distances) for each arc $(i,j)\in A$. The cost matrix C could be symmetrical, asymmetrical or Euclidean. The total set of points is divided as *V=V'UD* as d is the first point from *V*, makes the set of depots (*D*). At first, there are m_k salesmen in *k* depot while the total set of salesmen is *m*. the total intermediated points (cities) includes:

$V' = \{d+1, d+2, \ldots, n\}$

We have binary variable with 3 indicators x_{ijk} (notice that x_{iik} equals zero):

$$x_{ijk} = \begin{cases} 1 & \text{If a salesman who exits from k depot crosses (i,j) arc} \\ 0 & \text{Otherwise} \end{cases}$$

u_i indicated the total points which exist along the travel from depot to i point for each salesman (concluding depot), and L is the highest number if points where a salesman must visit. Thus, for each $i\geq 2$; we have: $1\leq u_i \leq L$

k is also the least numbers of points where one salesman must visit. It means that if x_{ijk} = 1, $K\leq u_i \leq L$ must be sustained. In figure 1, one mTSP problem with 5 cities and 2 salesmen is shown. Also in figure 2, one mTSP problem with 10 cities and 4 salesmen, 2 depots, and 2 salesmen in each depot is illustrated which indicated one response with 4 travels (one travel for each salesman):

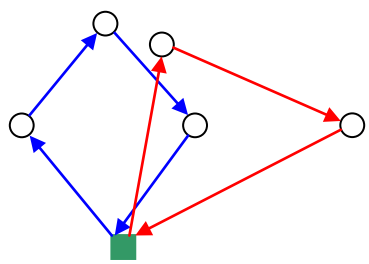


Figure 1: mTSP with 5 cities and 2 salesmen

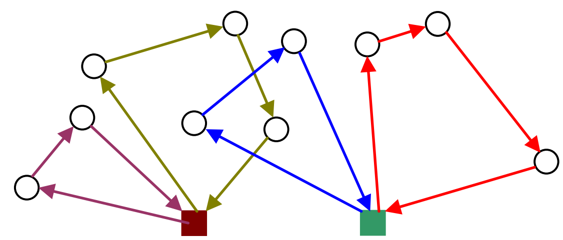


Figure 2: mTSP with 10 cities and 4 salesmen, 2 depots, and 2 salesmen in each depot

Formulation

This formulation for some traveling salesmen with fixed depots and destinations are as follow:

$$\text{Minimize} \quad \sum_{k\in D}\sum_{j\in V'}(c_{kj}x_{kjk}+c_{jk}x_{jkk})+\sum_{k\in D}\sum_{i\in V'}\sum_{j\in V'}c_{ij}x_{ijk}$$

S.t.

$$\sum_{j\in V'}x_{kjk}=m_k, \quad k\in D, \tag{1}$$

$$\sum x_{kjk}+\sum\sum x_{ijk}=1, \quad j\in V', \tag{2}$$

$$x_{kjk}+\sum_{i\in V'}x_{ijk}-x_{jkk}-\sum_{i\in V'}x_{jik}=0, \quad k\in D, \quad j\in V', \tag{3}$$

$$\sum_{j\in V'}x_{kjk}-\sum_{j\in V'}x_{jkk}=0, \quad k\in D, \tag{4}$$

$$u_i+(L-2)\sum_{k\in D}x_{kik}-\sum_{k\in D}x_{ikk}\leq L-1, \quad i\in V' \tag{5}$$

$$u_i+\sum_{k\in D}x_{kik}+(2-K)\sum_{k\in D}x_{ikk}\geq 2, \quad i\in V' \tag{6}$$

$$\sum_{k\in D}x_{kik}+\sum_{k\in D}x_{ikk}\leq 1, \quad i\in V', \tag{7}$$

$$u_i-u_j+L\sum_{k\in D}x_{ijk}+(L-2)\sum_{k\in D}x_{jik}\leq L-1, \quad i\neq j, \quad i,j\in V', \tag{8}$$

$$x_{ijk}\in\{0,1\}, \quad i,j\in V' \quad k\in D. \tag{9}$$

$$m\geq 1 \text{ and integer} \tag{10}$$

This formulation is valid in the case that $2 \le K \le \lfloor n/m \rfloor$ and $K \le L \le n-(m-1)K$ is feasible. Thus, one salesman can not leave one depot, visit only one city, and returns to the same depot. As the result, the number of cities one salesman must visit .without considering the depot, must be at least 2 cities .The first limitation guarantees that m_k salesmen exactly exist each $K \in D$ depot. The second limitation indicated that each point (city) is exactly visited once.

The unity of travels for intermediate points and depots are illustrated by the third and forth limitation respectfully. Limitations (5) and (6) apply the upper and lower limits of visited points to the travels. In general, if i is the first point in each travel, these limitations set u_i equals to 1. The travels with only one intermediated point are prohibited by (7) limitation. Finally, (8) limitation is subtour elimination constraint (SEC) that avoids the existence of any sub-travels (under-travel) among intermediated points. These sub-travels are some blocked travels which are made without any depot as start or end point by intermediate points. These could appear in the case that there would be no suitable SEC in responses. It obviously appears that this problem is related to NP-Hard (None-Deterministically Polynomial Time Problem). There are some eliminations in terms of the number of $O(dn^2)$ binary variable as well as $O(n^2)$ in this formulation.

One Genetic Algorithm for solving the Mathematical Model of VmTSP with Stable Depots and Destination

The purpose is to formulate one mathematical model of VmTSP with stable depots and destinations based on specific Genetic Algorithm. Hence, there will be one almost efficient response for medium average problems and one suitable response in one logical time for larger problems since we are not able to find an optimum response. In addition, we studied and compared various parameters of genetic algorithm. Six basic parameters must be identified for each genetic algorithm at first. Each formulated requires its own parameters genetically. The major parameters for the genetic algorithm specified for VmTSP model with stable depots and destinations are considered as follow:

Chromosome Illustration: The purpose of Chromosome illustration is offering one possible response for the problem. one Chromosome with a good design should eliminated or decreases repetitive responses, offers one suitable response for the problem, and provides suitable situation for the efficient performance of GA parameters to acquire better responses. Figure 3 is one recent design of chromosome for VmTSP illustrates 13 cities, 4 salesmen, 2 depots, and 2 salesmen each depot which has two separate parts. The first part of the chromosome is the permutation of numbers from 1 to n that indicates n cities. The length of second part of the chromosome is m that shows those specified cities for each m salesman. This part also illustrates that which salesmen leave the depots respectfully that indicated the first m_1 salesman is related to the first depot, second m_2 salesman is related to the second depot, and other depots indicate the same as follow. The specified numbers of the second part of Chromosome are m integer which is at least 2 while their total set of number equals to the number of cities (n).

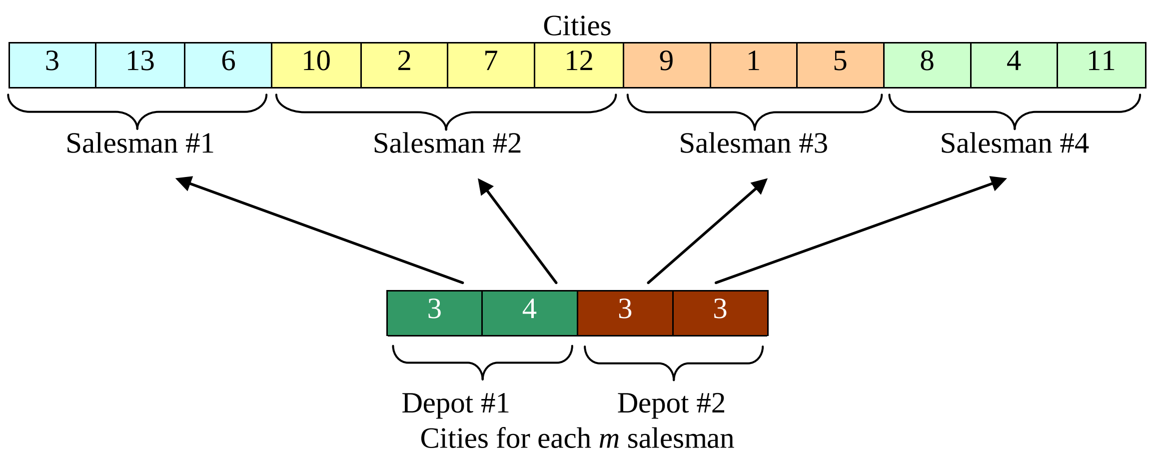


Figure 3. Chromosome for VmTSP illustrates 13 cities, 4 salesmen, 2 depots, and 2 salesmen each depot

The partially matched crosses over Parameter (PMX): In this parameter, two Childs are provided by two selected parents as one random place is chosen from two parents. Then, the genes related to the parents are substituted to be replaced in two Childs. The related number of this substituted gene in 1 parent as well as the related number of gene in the 2 parent is substituted with each other to be planted in saves. This practice is performed for almost half of the parents.

As an example in figure 4, the permutation number 4 was selected in the parent's chromosome and the related numbers of genes (7 and 9) are substituted. Then, number 9 in the first parent found to be substituted by number 7 in Second parent.

8	1	5	7	3	10	2	9	4	6	Parent #1
5	7	4	9	2	6	8	10	1	3	Parent #2
8	1	5	9	3	10	2	7	4	6	Parent #1
5	9	4	7	2	6	8	10	1	3	Parent #2

Figure 4. The partial matched crosses over Parameter (PMX)

Union Cross-over #2 parameter (UX#2): In this parameter, one salve is produced by two parents as one sub-branch of the available genes in parent 2 is planted under the sub-branch S_1 first. Then, the rest the parent genes are planted in sub-branch S_2 like the 1 parent. One of the sub-branches is chosen randomly. Next; the first available gene in the selected sub-branch is planted in the stable to delete it from sun-branch. This process is continued till all the available genes under these two sub-branches would be planted in two Childs. As an example, we have the same process in figure 5:

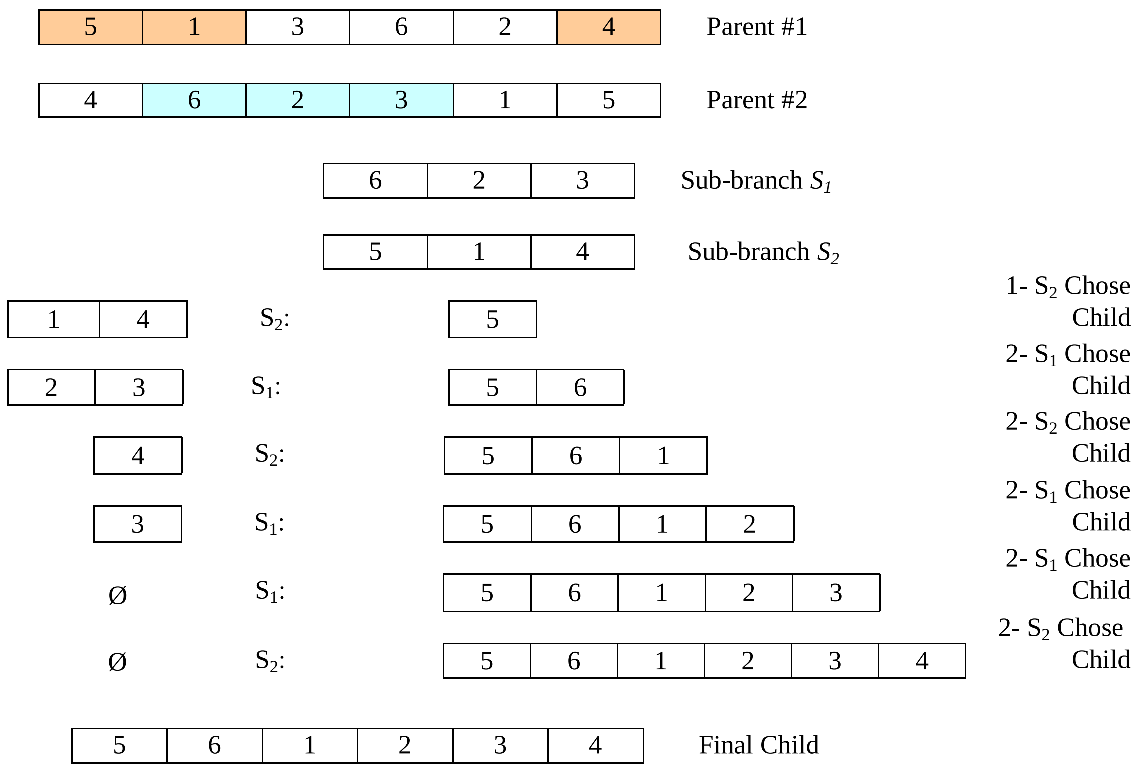
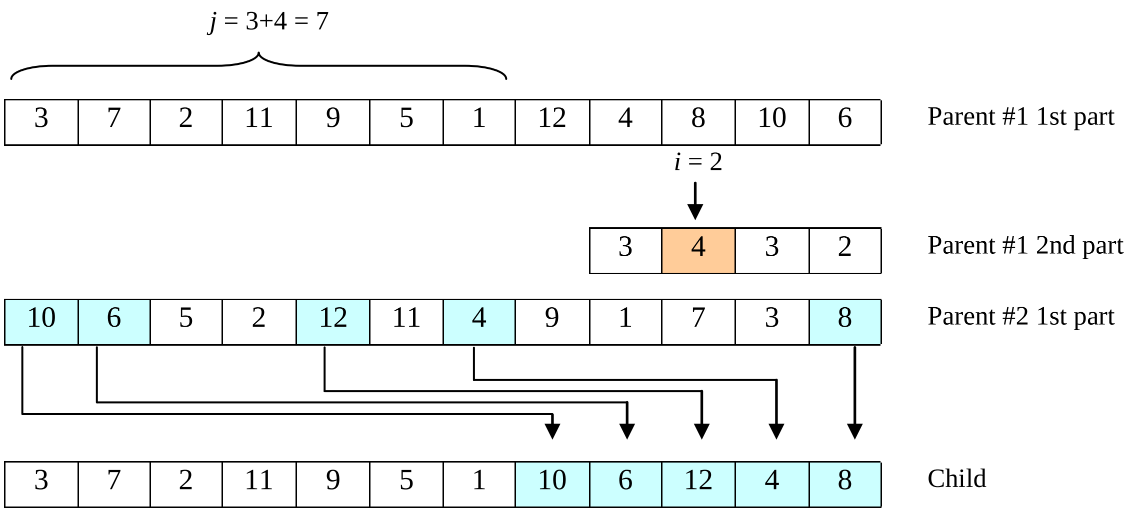


Figure 5. Union Cross-over #2 parameter (UX#2)

New Moonlight Cross-over Parameter (New-MX): In this parameter, one child is produces by two parents as we first choose one salesman randomly from the second part of chromosome of the first parent (one number between 1 and the number of salesmen) for instance *i*. Then, we plant the first *j* gene from the first parent in the child's chromosome respectfully as *j* would be the total *i* genes of the second part of the first parent. Finally, the rest, which don not exist in the child, are chosen from the second parent to be planted in the child (with the same order in 2 parent). One example of New-MX parameter is illustrated in figure 6. Suppose that there are two chromosomes (parent) with 12 cities, 4 salesmen, 2 depots, and 2 salesmen in each depot. First, choose one number between 1 and *m*-1 from the 1 parent randomly (*i*) that *i* is 2 in this example. *j* is the total travels related to the first *i* salesman from 1 parent which exists unchangeable in the salve. Therefore, we plant the first two travels in the child unchangeable. (The first 7 number of 1 parent is planted in the salve). Cities numbers 3, 7, 11, 9, 5 and 1 were already planted in the salves. Thus, these cities can not be added to the Childs. Finally, other numbers are chosen from the 2 parent which do not exist in the salve to be planted in the child respectably. (Numbers 10, 6, 12, 4 and 8 are added to the child.)



Mutation Parameter: Parameters 1 bit and 2-opt are used as mutation parameters for the production of generation randomly along with all cross-over parameters. The illustration of 1-bit and 2-opt parameters along the travels are provided in figure7. As you have noticed, in 1-bit method, two travels from two salesmen are chased randomly from one parent. Then, one point is deleted from the travel to be added to the other travel. In 2-opt method, two travels from two salesmen are chosen from one parent randomly, and two points (cities) of two travels are chosen randomly to be substituted.

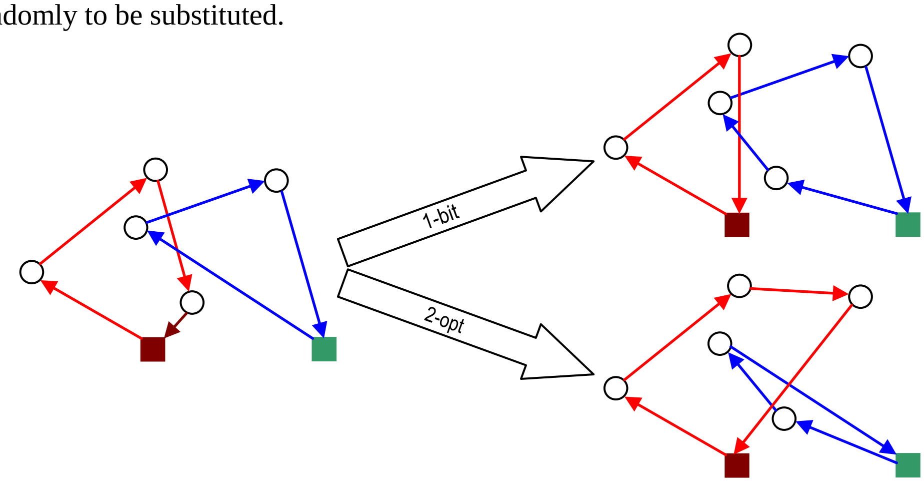


Figure 7. 1 bit and 2-opt Mutation Parameter

Evaluation and Comparing Methodology: Evaluating the efficiency of the explained genetic algorithm in the previous section, some sample problems were designed in small and average scales ($n \leq 70$) to compare the genetic algorithm with the optimum resolution. In the larger scales which exact methods cannot achieves some optimum solutions, Genetic algorithm can reach to some acceptable solutions. In addition, by performing 4 cross-over parameters and 3 selection strategy of different parents, we tried to achieve to the best solutions for some large scale parameters.

Since there are not some standard sample problems for VmTSP in the mathematical literature, one two-dimensional distance (cost) matrix is created as $C_{(d+n)\times(d+n)}$ among all the points (depots and cities) where C_{ij}(s) are with steady dispense in output [10,100] randomly. This distance matrix is stable with all the problems with the same number of cities (m) and same depots (d). Table 2 depicts different modes of the sample problem for 16 combinations of the size of the problem (n), the number of salesmen (m), the number of the depots (d), and the number of salesmen in each depot (m_k). All the salesmen start their travel from one random depot and finish it for each level of n. The number of salesmen is equal in each depot for all kinds of problems that equals to the number of salesmen (m) divided to the number of depots (m/d). The submission of the purpose is minimizing the total undertaken travels salesmen. Each salesman should visit at least 2 cities (except depot). There is no extra limitation for the maximum visited cities for each salesman. Considering the lowest limit (equals 2), the upper limit equals 2(m-1).

Table 2. Sample problems solved via genetic algorithm

ID	Number of Cities (n)	Number of Salesman (m)	Number of Depots (d)	Number of Salesman in each depot (m_k)
S_1*	40	2	2	1
S_2*	50	2	2	1
S_3*	60	2	2	1
S_4*	60	4	2	2
S_5*	70	2	2	1
S_6*	70	4	2	2
M_1	100	2	2	1
M_2	100	4	2	2
M_3	100	8	4	2
L_1	150	4	2	2
L_2	150	8	4	2
L_3	150	10	5	2
E_1	200	4	2	2
E_2	200	8	4	2
E_3	200	10	5	2
EX	350	8	4	2

* These problems solved via both genetic algorithm and branch and bound methods

Comparing the results of GA with Optimum Solution

Comparing the results of optimum solution by branch and bound methodology with Lingo v.8 software and the genetic algorithm result for the submission purpose of total distances is illustrated in Table 3. The final column of the table shows the variance percentage between optimum solution and GA responses which is measured by equation (11).

$$Gap\% = \frac{GA(fitness) - Lingo(fitness)}{Lingo(fitness)} \times 100 \qquad (11)$$

Table 3 - Comparing the results of optimum solution and the genetic algorithm

ID	Real results		GA results		Gap%
	Quantity	Time (s)	Quantity	Time (s)	
S_1	542	223	546	124	0.74
S_2	639	70	648	127	1.25
S_3	749	317	772	161	3.07
S_4	774	451	797	165	2.97
S_5	861	137	896	227	4.06
S_6	891	242	930	241	4.37

Considering the results of Table 3, it is clarified that we can achieve to some results quite approximate to optimum results in medium scale problems by the help of genetic algorithm in a shorter time though this contiguity of responses will eliminate by increasing the problem scale (Figure 8). Moreover, the comparing of the time of solving problems by genetic algorithm and optimum solution by branch and bound is illustrated in figure 9.

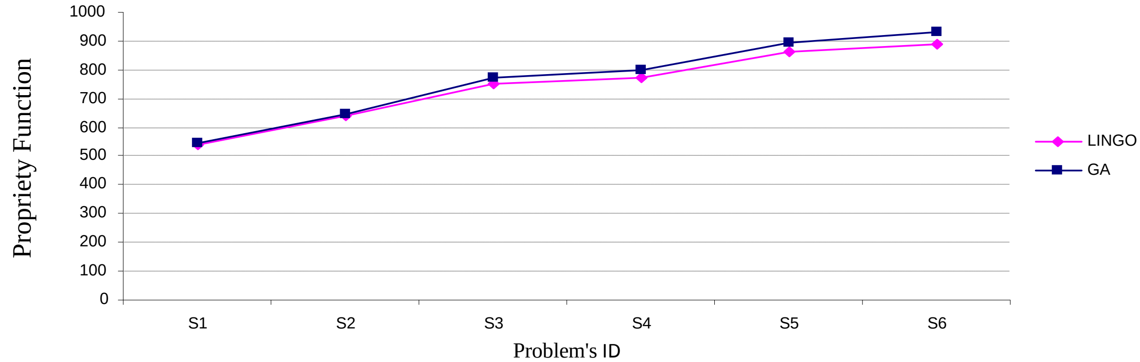


Figure 8 - Comparing the GA's propriety function vs. optimum solution in average scale problems

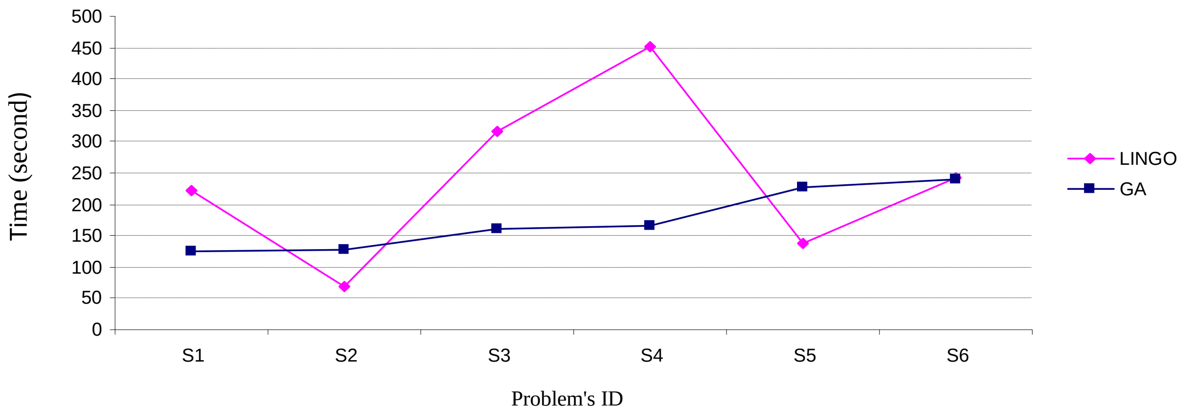


Figure 9 - Comparing the GA's time vs. optimum solution in average scale problems

In this section, we were able to compare the results achieved by GA and optimum solution by the capability of Lingo in solving the problems in this scale. For larger sale problems, the most important effective parameters in the explained genetic algorithm such as cross-over parameters as well as selections of parents are compared. According to the results of genetic algorithm, these two parameters (cross-over parameter and selection strategy of parent selection), were more effective comparing with other parameters in GA. Any changes in them resulted some more changes in the algorithm responses.

Comparing Cross-over parameter and Parent selection strategy in GA

In this section, the results of the performing GA by cross-over parameters and selection strategy of different parents are offered. The considered cross-over parameters include:

New-MX, OX, PMX and UX#2.

The parent selection strategy also includes:

Elitism strategy, Roulette wheel and Tournament Selection strategy

Comparing the results generally with all cross-over parameters and selection strategies for the problems with one similar scale, the mean propriety for the problems in largish scale, large scale, and extra large scale are shown in 10,11 and 12 graphs based on the kind of cross-over parameter and parent selection strategy.

Considering figure 10, it is shown that cross-over parameter UX#2 with elitism parent selection strategy has the best mean propriety submission in largish scale problems (problems with M_1, M_2 and M_3 indicators). As the result, the best function of GA explained in largish scale problems is UX#2 cross-over parameter and elitism parent selection strategy along with other shared parameters described in the sixth part. Similarly, figure 11 can depot the New-MX cross-over parameter with tournament parent selection strategy has the best mean propriety in large scale problems (problems with L_1, L_2 and L_3 indicators).Thus, The best performance of GA in terms of large scale problem is New-MX cross-over parameter and tournament parent selection strategy along with other shared parameters described in part six. Figure 12 also illustrates that PMX cross-over parameter with tournament selection strategy has the best mean propriety in extra large scale problem (problems with E_1, E_2 and E_3 indicators). As the final result, the best performance of GA in terms of extra large scale problems is PMX cross-over parameter and tournament parent selection strategy along with other shared parameters described in part six.

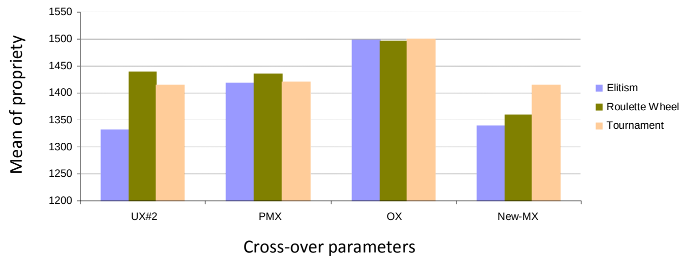


Figure 10- Comparing the propriety function of parameters with various selection strategies in largish scale problems (*n*=100)

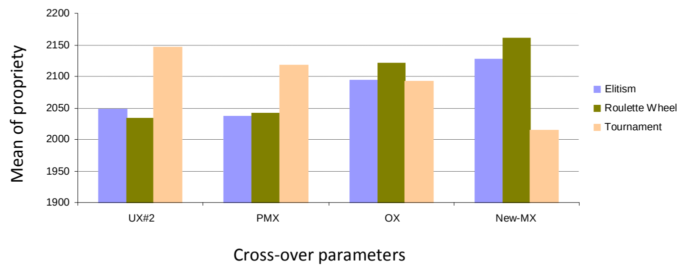


Figure 11- Comparing the propriety function of parameters with various selection strategies in large scale problems (*n*=150)

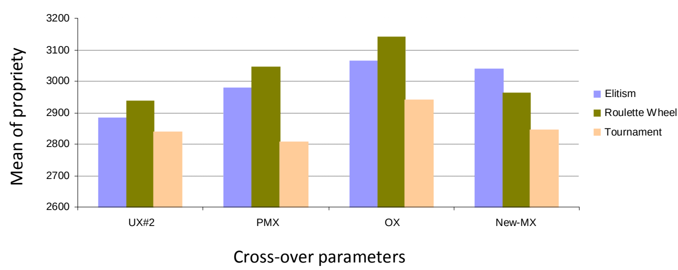


Figure 12- Comparing the propriety function of parameters with various selection strategies in extra large scale problems (*n*=200)

CONCLUSION

In this chapter, Genetic algorithm was first introduced as one of randomly search methods. These algorithms search the sample problems by the help of performing its parameters on group of possible solutions for finding approximate optimum solutions. The important parameters in creating GA are the mode of chromosome illustrations based on the given model, the method of designing the parameters as well as parent selection strategy. Then, the models related to VmTSP with fixed depots and destinations are offered. The purpose of this model is finding the possible travels for each salesman as to minimize the total undertaken distances by each salesman. Then, one heuristic genetic algorithm was offered for solving this problem. We noticed that evaluating the achieved results, Performing GA comparing with optimum results by branch and limit methodology had a small difference in small and medium scale problem. The time was also better than the achieved time of optimum solution. Although this exact method is not able to achieve to optimum result gently by increasing the scale of the problem, the presented genetic algorithm can achieved some acceptable results for problems with the scale of 350 cities.

REFERENCES

Tolga B. (2006), “The multiple traveling salesman problem: an overview of formulations and solution procedures”, *Omega*, 34:209–219.

Yu Z, Jinhai L, Guochang G, Rubo Z, Haiyan Y. (2002), “An implementation of evolutionary computation for path planning of cooperative mobile robots”, *Proceedings of the fourth world congress on intelligent control and automation*, vol.3.

András K, János A., (2011), “Optimization of Multiple Traveling Salesmen Problem by a Novel Representation based Genetic Algorithm”, *University of Pannonia, Department of Process Engineering*, P.O. Box 158. Veszprém H-8200, HUNGARY

Bektas T, (2005), “The multiple traveling salesman problem: an overview of formulations and solution procedures”, *Department of Industrial Engineering, Baskent University, Baglica Kampusu, Eskisehir Yolu 20. km., 06530 Ankara, Turkey*

Kara I, Bektas T. (2006), “Integer programming formulations of multiple salesman problems and its variations”, *European Journal of Operational Research*, 174, 1449-1458.

Arthur E. Carter and Cliff T. Ragsdale. (2006), “A new approach to solving the multiple traveling salesperson problem using genetic algorithms”, *European Journal of Operational Research*, 175:246–257.

Yousefikhoshbakht, M, Sedighpour, M, (2012), “A Combination of Sweep Algorithm And Elite Ant Colony Optimazition For Solving The Multiple Traveling Salesman Problem”, *The Publishing House of The Romanian Academy, Proceedings of The Romanian Academy*, Series A, Volume 13, Number 4/2012, pp. 295–301

Gromicho J, Paixão J, Branco I. (2010), “Exact solution of multiple traveling salesman problems”, *Combinatorial optimization*, NATO ASI Series, vol. F82. Berlin, Springer, p, 291- 292.

Russell RA. (1977), “An effective heuristic for the m-tour traveling salesman problem with some side conditions”, *Operations Research*, 25(3), 517-524.

Lin S, Kernighan B. (1973), “An effective heuristic algorithm for the traveling salesman problem”, *Operation Research*, 21 , 498 – 516.

Carlos E. De Andrade, FL´Avio Keidi Miyazawa, Mauricio G. C. Resende., (2013), “Evolutionary Algorithm For The k-Interconnected Multi-Depot Multi-Traveling Salesman Problem”, *AT&T Labs Research Technical Report* , March 1, 2013

Fogel DB. (2008), “A parallel processing approach to a multiple traveling salesman problem using evolutionary programming”, *In: Proceedings of the fourth annual symposium on parallel processing* .Fullerton, CA, p, 318 – 326.

Wacholder E, Han J, Mann RC. (1989), “A neural network algorithm for the multiple traveling salesmen problem". *Biology in Cybernetics*, 61, 11 – 19.

Somhom S, Modares A, Enkawa T. (1999), “Competition-based neural network for the multiple traveling salesmen problem with minmax objective”, *Computers and Operations Research*, 26(4), 395 – 407.

Hsu C, Tsai M, Chen W. (1991), “A study of feature-mapped approach to the multiple traveling salesmen problem”, *IEEE International Symposium on circuits and Systems*, 3, 1589 – 1592.

Vakhutinsky IA, Golden LB. (1994), “Solving vehicle routing problems using elastic net”, *Proceedings of the IEEE international conference on neural network*, p, 4535 – 4540.

Modares A, Somhom S, Enkawa T. (1999), “A self-organizing neural network approach for multiple traveling salesman and vehicle routing problems”. *International Transactions in Operational Research*, 6, 591 – 606.

Tang L, Liu J, Rong A, Yang Z.(2000), “A multiple traveling salesman problem model for hot rolling scheduling in Shangai Baoshan Iron & Steel Complex”, *European Journal of Operational Research*, 124, 267 – 82.

Song C, Lee K, Lee WD.(2003), “Extended simulated annealing for augmented TSP and multi-salesmen TSP”, *Proceedings of the international joint conference on neural networks*, vol. 3, p, 2340 – 2343.

Gomes LTD, Von Zuben FJ. (2009), “Multiple criteria optimization based on unsupervised learning and fuzzy inference applied to the vehicle routing problem”, *Journal of intelligent and Fuzzy Systems*, 13, 143 – 154.

Sofge D, Schultz A, De Jong K. (2002), “Evolutionary computational approaches to solving the multiple traveling salesman problem using a neighborhood attractor schema” *Lecture notes in computer science*, vol. 2279, Berlin, Springer, p, 151 – 160.

Belmore M, Hong S. (1974), “Transformation of multi-salesmen problem to the standard traveling salesman problem”, *Journal of association for computing Machinery*, 21, 500 – 504.

Hong S, Padberg MW. (1997), “A note on the symmetric multiple traveling salesman problem with fixed charges”, *Operations Research*, 25(5), 871 – 874.

Rao MR. (1980), “A note on the multiple traveling salesman problem”, *Operations Research*, 28(3), 628 – 632.

Junker R, Volgenant T. (1988), “An improved transformation of the symmetric multiple traveling salesman problem". *Operations Research*, 36(1), 163 – 167.

Laporte G, Nobert Y, Taillefer S. (1988), "Solving a family of multi-depot vehicle routing and location-routing problems", *Transportation Science*, 22(3), 161 – 172.

GuoXing Y. (1995), "Transformation of multidepot multisalesmen problem to the standard traveling salesman problem", *European Journal of Operational Research*, 81, 557 – 560.

Ali AI, Kennington JL. (1986), "The asymmetric m-traveling salesmen problem: a duality based branch-and-bound algorithm", *Discrete Applied Mathematics*, 13,259 – 276.