Artificial Intelligence to Solve Travelling Salesman Problem with Weighted Multiobjective

Manal G. Ahmed, Faez H. Ali, Safanah F. Yousif and Aseel A. Jawad

Mathematics Department, College of Science, Mustansiriyah University, Baghdad, Iraq

Abstract—**This paper examines the Weighted Multiobjective Travelling Salesman Problem (WMTSP), presents particular examples of the problem, and suggests using two local search techniques: Bees Algorithm (BA) and Particle Swarm Optimization (PSO) to identify the best solutions for each strategy. The findings demonstrate that the Exact approach receives closed results from BA and PSO, and that they are closed to one another.**

Keywords— Bees Algorithm, Particle Swarm Optimization, Travelling Salesman Problem, Artificial Intelligence. Multiobjective Functions.

I. INTRODUCTION

One of the most important problems of combinatorial optimization problems is the Traveling Salesman Problem (TSP) which is a challenge of determining the lowest cost to visit a group of cities in a specific order, starting and ending in the same place, and requiring that each city be visited precisely once. The core of the problem was in the field of CO since it was expressed theoretically (Birdawod, 2022). As general form the TSP is asymmetric in data (Nawkhass & Birdawod, 2017). This type of issue comes up when we deal with the time and expense of traveling between places rather than the actual distances between cities (Subhi & Ibrahim, 2018). The difficulty of determining the path with the lowest cost and the time required to reach the solution make TSP an NP-hard task (Alazzam, Alsmady , & Mardini, 2020). In computer science, the TSP is a common car routing problem (TSP). One important and well-known COP is TSP. The Hamiltonian route problem (HRP), in which a path in an undirected or directed graph is committed to visiting every vertex exactly once, is comparable to TSP (Abed and Al-Salami, 2021). In contrast, TSP is about a salesman who is supposed to travel by going to every city that is provided exactly once and then taking the quickest route back to the beginning point (Hung, 2016).

On TSP, local search methods (LSMs) have been the subject of numerous investigations. PSO method, one of the primary optimization approaches, is used in Zhiping (Zhiping, 2017) suggested solution, which uses a multiobjective strategy. Since the conventional PSO algorithm has a tendency to show slow convergence rates and is vulnerable to local minimum problems, this approach is based on augmented cultural mechanisms. The proposed algorithm gives minimal local value occurrences with high convergence. Shuai et al. (Shuai, Yunfeng, & Kai, 2019) investigated the MTSP in 2019 and used the Genetic Algorithm (GA) to identify a viable solution. They suggested adopting the NSGA-II framework because some of the good GA operators minimum objective function of distance, and minimum range between all salesmen. The resulting solution is well-convergent, well-diversity non-dominated, and good (perhaps optimal). The suggested algorithms' efficiency and efficacy in solving the MTSP are demonstrated by comparing their results with those of several state-of-the-art techniques (Jameel and Al-Salami, 2023).

Jasim and Ali in 2019 (Jasim & Ali, 2019) they proposed two LSM: Simulated Annealing (SA) and Genetic Algorithm (GA) with improved GA (IGA) and Hybrid GA (HGA) to enhanced the results of SA and GA to solve TSP. HGA proved its efficiency compared with other methods for $5 \leq n \leq 2000$. In 2022, Ahmed and Ali (Ahmed & Ali, The Best Efficient Solutions for Multi-Criteria Travelling Salesman Problem Using Local Search Methods, 2022) proposed two LSMs to tackle the Multi-Criteria TSP (MCTSP) and obtain good solutions: the BA and PSO. The outcomes of the PSO and BA were contrasted with those of several heuristic techniques and accurate techniques like BAB and complete enumeration (Faaeq et al., 2018; Zaidan et al, 2024). The results showed that for a high number of nodes (n), the two LSMs approaches were effective. Furthermore, for n≤700 jobs in a reasonable amount of time, the suggested LSMs offered the most effective solutions for the MCTSP (Al-Salami et al., 2023; Alsammarraie et al., 2024).

The portions of this paper are as follows: The Weighted Multiobjective Traveling Salesman Problem (WMOTSP) formulation is shown in section 2. Section 3 proves the problem's exceptional situations. Section 4 discusses a few LSMs. Section 5 compares the outcomes of the LSMs employed in this paper with a few heuristic and exact approaches. Section 6 concludes with a discussion and recommendations based on the findings.

DOI: http://doi.org/10.24086/icafs2025/paper.1765

II. Mathematical Formulation of the WMOTSP

The mathematical model of WMOTSP is as follows:

Min $Z = \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$

Subject to:

$$\left.\begin{aligned} &\sum_{j=1}^{n} x_{ij} = 1,\ i = 1,2,\dots,n. \\ &\sum_{i=1}^{n} x_{ij} = 1,\ j = 1,2,\dots,n. \\ &w_t = 1 - w_d \\ &x_{ij} \in \{0,1\}. \end{aligned}\right\} \dots(WMOTSP)$$

For new weights we choose w_d=0.33, 0.5, 0.67. The matrix notation of the objective function (OBF) of problem ($WMOTSP$) can be written as follows: Let and $T = [t_{ij}]_n$ be the time matrix, $D = [d_{ij}]_n$ be the distance matrix, while $X = [x_{ij}]_n$, $i,j = 1,2,\dots,n$, be the adjacency matrix ($X = G(A)$) of the graph G of the problem ($WMOTSP$).

Now let $\sigma = \{\rho_1,\rho_2,\dots,\rho_{n-1}\}$, be a vector with length $(n-1)$, sequence solution where $\pi \in S, S$ is the set of all feasible solutions ($WMOTSP$). Suppose we start with an end at city 1, when $\rho_j \in \{2,3,\dots,n\}$, then the total OBF cost can be written as:

$V_C = c_{1,\sigma(1)} + \sum_{i=1}^{n-2} c_{\sigma(i),\sigma(i+1)} + c_{\sigma(n-1),1}$

$V_C = c_{1,\sigma(1)} + c_{\sigma(n-1),1} + \sum_{i=1}^{n-2} c_{\sigma(i),\sigma(i+1)}$ …(1)

Where V_C is the cost of distance (V_d) or cost of time (V_t), and $c_{ij} = d_{ij}$ or t_{ij}.

Then the objective function Z of $MCTSP$-problem can be stated as follows:

Minimize $V = \left(d_{1,\sigma(1)} + \sum_{i=1}^{n-2} d_{\sigma(i),\sigma(i+1)} + d_{n-1,1}, t_{1,\sigma(1)} + \sum_{i=1}^{n-2} t_{\sigma(i),\sigma(i+1)} + t_{n-1,1}\right)$ …(2)

Relation (2) will describe the cost of WMOTSP which is called WMOTSP_COST algorithm. the **WMOTSP_COST** is as follows:

Algorithm (0): WMOTSP_COST (σ)

Step(1):INPUT: $n, \sigma,\ T = [t_{ij}], D = [d_{ij}],\ i,j = 1,2,\dots,n, w_d, w_t = 1 - w_d$.

Step(2): $V(1) = T(1,\sigma(1)) + T(\sigma(n),1)$;

Step(3): FOR $j = 1{:}n-2$

$V(1) = V(1) + T(\sigma(j),\sigma(j+1))$;

ENDFOR $\{j\}$

Step(4): $Z(1) = D(1,\sigma(1)) + D(\sigma(n),1)$;

Step(5): FOR $j = 1{:}n-2$

$V(2) = V(2) + D(\sigma(j),\sigma(j+1))$;

ENDFOR $\{j\}$

Step(6): **OUTPUT**: $V = w_t V(1) + w_d V(2)$

Step(7): END.

III. Special Cases for WMOTSP

Case (1): If $d_{ij} = d,\ \forall i,j = 1,2,\dots,n$, then the OBF is:

$$\mathbf{V} = \left(\boldsymbol{n.w_d.d + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}}\right)$$

Proof:

$$V = \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$$
$$= \left(w_d.d \sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$$
$$= \left(w_d.d.n + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right) = \left(n.w_d.d + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$$

Case(2): If $t_{ij} = t\ \ \forall i,j = 1,2,\dots,n$, then the OBF is

$$\mathrm{V} = w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + n.w_t.t$$

Proof:

$$V = \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$$
$$= \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t.t \sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}\right)$$
$$= \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t.t.n\right) = \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + n.w_t.t\right)$$

From case (1) and (2), the WMOTSP becomes constant plus single objective and we can use all the methods for single objective to find the optimal and approximate solutions.

Case(3): If $d_{ij} = d$ and $t_{ij} = t\ \ \forall i,j = 1,2,\dots,n$, the WMOTSP becomes

$$Z = \left(w_d \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} + w_t \sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}\right)$$
$$= \left(w_d.d.\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} + w_t.t \sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}\right)$$
$$= (w_d.d.n + w_t.t.n) = n(w_d.d + w_t.t).$$

For this case any sequence is optimal sequence, so we have (n-1)! sequences.

IV. Using LSMs to Solve WMOTSP

To identify the best solutions for WMOTSP, we have employed two LSMs in this section: PSO and BA. Generally speaking, LSMs work well for COP, particularly in big cities (RibeiroKyle & Schlansker, 2003).

A. *Particle Swarm Optimization (PSO)*

Particle Swarm Optimization (PSO) is a technique that has a lot of applications. In general, PSO is a good fit for any application area where other evolutionary techniques excel (Shi, 2004). Kennedy and Eberhard were the first researchers to develop Particle Swarm Optimization (PSO) in 1995. PSO was first developed in 1995 by Kennedy and Eberhard (Zhiping, 2017). PSO uses the information provided within a swarm to improve an objective function. Every individual, or particle, is a possible remedy. The best solution, also known as the global best, is known to these solutions, and they modify their location and velocity accordingly. The objective function for every solution is formed by this interaction. Based on their locations and velocities inside the swarm, we then investigate various solutions to determine which is the best (Cergibozan, 2013).

B. *Bees Algorithm (BA)*

Artificial intelligence (AI) is being utilized to investigate distributed issue solving without the usage of a centralized control system. This is regarded as a superior option than centralized, rigid, and preprogrammed control. In ant colonies, beehives, bird flocks, and animal herds, real-life Swarm Intelligence (SI) can be observed.

To overcome the challenges, the population's self-organization behavior must be changed. The BA is an improvement method that finds the optimal solution by analyzing the foraging behavior of honey bees (Pham, Ghanbarzadeh, Koc, & Otri, 2006).

DOI: http://doi.org/10.24086/icafs2025/paper.1765

V. Practical Results of Applying LSMs for Solving problem (WMOTSP)

For using LSMs, we suggested:

LSM(0) : The 1st and 2nd solutions of the Population are generated by MDTM and MTDM (Ahmed, Ali, Khalaf, & Sabri, 2023) respectively, while the others are generated randomly.

LSM(1) : The population generated randomly.

To run the PSO and BA we use 100, 500 and 1000 iterations for $n = 5, \dots, 10$, for $n = 11, \dots, 40$ and for $n = 60, \dots, 8000$ respectively. PSO and BA have population size (20) solutions as initial population, for PSO: C_1=$C_2 = 2$, V_{max}=2, $V_{min} = -V_{max}$=-2. For BA: mm = 5, ee = 2, nep =5, nsp = 3. For three kinds of weights, we denote (0.33,0.67) by w1, (0.67,0.33) by w2 and (0.5,0.5) by w3.

Four results tables are introduced to compare the results. Table 1 and Table 2 shows the comparison just between the PSO and BA, table 3 between them with BAB, tables 4 and 5 between them and other heuristic methods.

TABLE 1
Comparison between PSO(0) and PSO(1) for problem (WMOTSP) , $n = 5 : 1000$.

n	w_i	PSO(0)		PSO(1)	
		$Av(V_{ap})$	AT	$Av(V_{ap})$	AT
5	w1	20.1	R	20.1	*R*
	w2	18.6	R	18.6	*R*
	w3	19.6	R	19.6	*R*
10	w1	34.8	R	35.6	R
	w2	33.6	R	34.5	R
	w3	34.3	R	34.4	R
40	w1	98.4	1.1	170.4	1.1
	w2	91.0	1.1	162.9	1.1
	w3	95.6	1.1	173.9	1.1
60	w1	116.9	3.1	275.8	3.2
	w2	117.0	3.2	258.8	3.2
	w3	122.5	3.2	275.4	3.2
80	w1	149.3	4.2	387.7	4.1
	w2	139.2	4.1	364.1	4.2
	w3	150.4	4.2	383.6	4.2
100	w1	168.8	3.9	499.1	3.9
	w2	168.4	3.9	466.9	3.9
	w3	178.3	3.9	490.1	3.9
300	w1	383.4	11.6	1614.9	11.7
	w2	375.2	11.7	1537.0	11.7
	w3	389.9	11.6	1586.4	14.4
500	w1	580.1	19.5	2761.7	19.6
	w2	581.5	19.6	2645.1	19.6
	w3	595.7	19.6	2701.3	19.6
700	w1	786.0	27.6	3902.4	27.5
	w2	785.4	27.6	3744.5	27.4
	w3	790.0	27.6	3820.7	27.8
900	w1	982.3	35.2	5045.7	35.7
	w2	977.3	34.6	4864.7	34.7
	w3	994.8	34.8	4963.8	35.3
1000	w1	1089.2	39.3	5625.2	39.4
	w2	1079.9	39.7	5418.8	39.5
	w3	1091.0	39.4	5537.1	39.4

TABLE 2
Comparison between BA(0) and BA(1) for problem (WMOTSP) , $n = 5 : 1000$.

n	w_i	BA(0)		BA(1)	
		$Av(V_{ap})$	AT	$Av(V_{ap})$	AT
5	w1	20.1	*R*	20.1	*R*
	w2	18.6	*R*	18.6	*R*
	w3	19.6	*R*	19.6	*R*
10	w1	35.5	R	35.6	R
	w2	33.9	R	34.9	R
	w3	34.8	R	35.8	R
40	w1	97.1	R	171.2	R
	w2	89.8	R	158.9	R
	w3	93.7	R	166.7	R
60	w1	115.8	R	269.8	R
	w2	115.7	R	254.9	R
	w3	121.7	R	263.0	R
80	w1	148.8	R	375.9	R
	w2	139.2	R	355.9	R
	w3	150.3	R	366.0	R
100	w1	167.8	R	484.7	R
	w2	167.9	R	455.1	R
	w3	177.5	R	473.7	R
300	w1	383.4	R	1597.4	R
	w2	375.0	R	1521.1	R
	w3	389.9	R	1576.6	R
500	w1	580.1	1.1	2740.9	1.1
	w2	579.6	1.1	2610.6	1.1
	w3	595.4	1.1	2684.8	1.1
700	w1	784.7	1.5	3862.2	1.5
	w2	784.9	1.5	3726.8	1.5
	w3	789.0	1.5	3802.9	1.5
900	w1	982.3	2.0	5025.3	1.9
	w2	976.0	1.9	4841.8	1.9
	w3	993.5	1.9	4939.3	1.9
1000	w1	1088.4	2.2	5616.0	2.1
	w2	1079.9	2.2	5379.2	2.1
	w3	1091.0	2.2	5516.0	2.1

TABLE 3
Comparison between BAB (Ahmed, Ali, Khalaf, & Sabri, 2023), PSO(0) and BA(0) for problem(WMOTSP), $n = 4{:}22$.

n	w_i	BAB		PSO(0)		BA(0)	
		$Av(V_{ap})$	AT	$Av(V_{ap})$	AT	$Av(V_{ap})$	AT
4	w1	19.1	*R*	19.1	*R*	19.1	*R*
	w2	18.9	*R*	18.9	*R*	18.9	*R*
	w3	19.3	*R*	19.3	R	19.3	*R*
MV		19.1	*R*	19.1	*R*	19.1	*R*

DOI: http://doi.org/10.24086/icafs2025/paper.1765

8	w1	31.2	R	31.2	R	31.2	R
	w2	29.2	R	29.2	R	29.2	R
	w3	30.6	R	30.6	R	30.6	R
MV		30.3	R	30.3	R	30.3	R
12	w1	35.1	23.5	39.5	R	38.7	R
	w2	33.5	23.1	37.8	R	36.1	R
	w3	34.9	22.9	40.1	R	39.2	R
MV		34.5	23.2	39.1	R	37.9	R
16	w1	40.9	127.6	46.2	R	46.2	R
	w2	37.4	1.5	47.4	R	47.6	R
	w3	41.0	10.6	47.7	R	47.2	R
MV		39.8	46.6	47.1	R	46.9	R
20	w1	47.4	86.3	58.8	R	56.8	R
	w2	45.1	1.10	58.2	R	54.9	R
	w3	47.2	7.6	59.0	R	57.1	R
MV		46.8	46.6	58.7	R	56.2	R
22	w1	54.2	27.8	64.7	R	62.5	R
	w2	49.9	41.4	65.3	R	63.7	R
	w3	53.5	436.7	63.9	R	61.5	R
MV		52.6	168.7	64.6	R	62.6	R

From TABLE 3, we notice that BA(0) is more accurate to BAB than PSO(0).

The comparison between the results of PSO(0) and BA(0) with BAB are shown in Fig. (1).

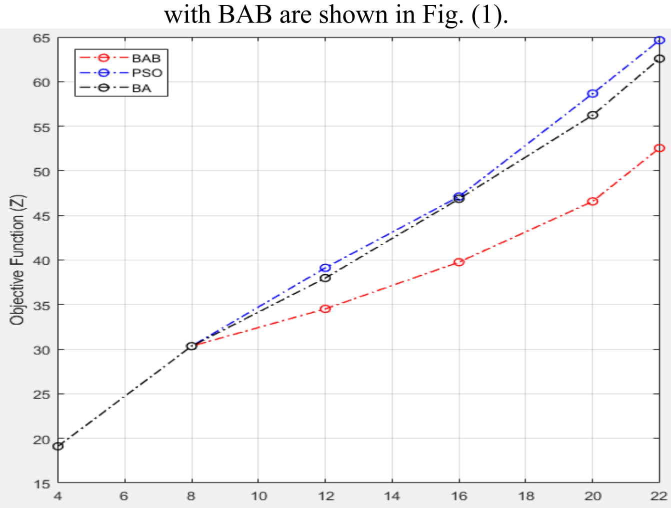

Fig. (1): Comparison between BAB [12], PSO(0) and BA(0) for problem (WMOTSP), for different n.

TABLE (4)

Comparison PSO(0) and BA(0) with MMDA (Ahmed, Ali, Khalaf, & Sabri, 2023) for problem (WMOTSP), $n = 100{:}700$.

n	w_i	MMDA		PSO(0)		BA(0)	
		$Av(V_{ap})$	AT	$Av(V_{ap})$	AT	$Av(V_{ap})$	AT
100	w1	138.4	1.9	168.8	3.9	167.8	R
	w2	136.2	1.3	168.4	3.9	167.9	R
	w3	142.7	1.9	178.3	3.9	177.5	R
300	w1	317.0	36.6	383.4	11.6	383.4	R
	w2	318.8	32.8	375.2	11.7	375.0	R
	w3	323.8	26.2	389.9	11.6	389.9	R
500	w1	506.3	328.4	580.1	19.5	580.1	1.1
	w2	507.0	330.9	581.5	19.6	579.6	1.1
	w3	509.4	339.1	595.7	19.6	595.4	1.1
700	w1	704.2	1254.1	786.0	27.6	784.7	1.5
	w2	703.4	1307.0	785.4	27.6	785.0	1.5
	w3	704.1	1262.1	790.0	27.6	789.0	1.5

TABLE 5

Comparison between MMDTM (Ahmed, Ali, Khalaf, & Sabri, 2023), PSO(0) and BA(0) for problem (WMOTSP), $n = 1000{:}8000$.

n	w_i	MMDTM		PSO(0)		BA(0)	
		$Av(V_{ap})$	AT	$Av(V_{ap})$	AT	$Av(V_{ap})$	AT
1000	w1	1091.9	R	1089.1	39.3	1088.4	2.2
	w2	1080.7	R	1079.9	39.7	1079.9	2.2
	w3	1091.0	R	1091.0	39.4	1091.0	2.2
2000	w1	2089.1	R	2077.9	81.5	2077.5	9.1
	w2	2078.6	R	2081.9	81.9	2081.9	5.6
	w3	2095.4	R	2086.8	80.7	2086.8	9.0
3000	w1	3085.0	R	3084.1	128.5	3084.1	12.7
	w2	3079.6	R	3079.6	129.2	3078.9	8.3
	w3	3090.0	R	3090.0	127.0	3089.2	7.1
4000	w1	4093.9	R	4092.7	207.2	4092.7	11.3
	w2	4084.7	R	4082.5	160.5	4082.5	13.3
	w3	4097.0	R	4097.0	163.0	4096.6	34.4
5000	w1	5088.9	R	5084.1	207.9	5084.1	15.1
	w2	5086.0	R	5085.8	208.9	5084.4	14.9
	w3	5097.2	R	5097.2	210.7	5097.2	15.1
6000	w1	6084.3	1.2	6083.5	241.3	6083.3	22.4
	w2	6082.2	1.2	6082.2	244.1	6082.2	25.7
	w3	6094.9	1.2	6094.9	247.5	6094.8	53.3
7000	w1	7086.8	1.9	7085.0	292.4	7085.1	26.0
	w2	7084.5	1.7	7084.5	289.3	7084.5	26.6
	w3	7094.0	2.5	7093.0	284.5	7093.0	25.6
8000	w1	8085.8	2.6	8083.4	375.7	8083.4	51.7
	w2	8081.5	2.3	8081.5	348.5	8081.5	31.9
	w3	8091.9	2.2	8091.2	334.4	8091.2	40.4

From TABLE 5, we notice that BA(0) is the best method then PSO(0) and MDTM.

Note: In Table (4.15) we notice that MMDA is didn't solve the problem in reasonable time for $n =$ 900 and 1000.

VI. Conclusion

1) We proved some important special cases for our problem to convert the complexity of our problem from NP-hard to P-type.
2) We proposed two LSMs for WMOTSP to find approximate solution such as PSO and BA
3) we compare these methods with exact method BAB from $n = 4{:}22$ and we compare the results of PSO and BA with MMDA for to n=700 and MDTM up to $n = 8000$ to prove the efficiency of LSMs.
4) From Fig. (1) we can concluded that the results of BA are very closed to PSO, but it better than PSO.
5) We suggested use other methods of LSMs such as Genetic Algorithms (GA) or Simulated Annealing (SA).

DOI: http://doi.org/10.24086/icafs2025/paper.1765

6) To improve the performance of PSO and BA, we suggest making a hybrid between these algorithms from one side, or between them and another local search algorithms (e.g. SA or GA), from the other side.

References

Abed, F., & Al-Salami, Q. H. (2021). Calculate the best slope angle of photovoltaic panels theoretically in all cities in Turkey. International Journal of Environmental Science and Technology, 1-16.

Ahmed, M. G., & Ali, F. H. (2022). The Best Efficient Solutions for Multi-Criteria Travelling Salesman Problem Using Local Search Methods. *Iraqi Journal of Science, 63*(10), 4352-4360. doi:10.24996/ijs.2022.63.10.21

Ahmed, M. G., Ali, F. H., Khalaf, W. S., & Sabri, M. G. (2023). Solving Weighted Multiobjective Travelling Salesman Problem. *4th International Conference on Administrative & Financial Sciences, Gihan University.* Erbil - Kurdstan. doi:10.24086/ICAFS2023/paper.899

Alazzam, H., Alsmady , A., & Mardini, W. (2020). Solving Multiple Traveling Salesmen Problem using Discrete Pigeon Inspired Optimizer. *11th International Conference on Information and Communication Systems (ICICS),* (pp. 209-213). Arbid - Jordan: IEEE. doi:https://doi.org/10.1109/ICICS49469.2020.239528

Alsammarraie, O., H Al-Salami, Q., & Q Al-Salami, N. (2024, July). Transforming Coordinate Function Points Into 2D or 3D Graphics: An Algorithmic Approach. In 5th International Conference on Communication Engineering and Computer Science (CIC-COCOS'24) (pp. 336-341). Cihan University-Erbil.

Al-Salami, Q. H., El-Zelawi, F. I., & Sultan, A. S. (2023). Customer satisfaction on quality of ISO standard 9126 services in electronic banking in Libya. Cihan University-Erbil Journal of Humanities and Social Sciences, 7(1), 58-67.

Birdawod, H. Q. (2022). Using factor analysis to determine the most important factors affecting student absenteeism at Cihan University-Erbil. *Cihan University-Erbil Scientific Journal*, *6*(2), 1-8.

Cergibozan, C. (2013). Metaheuristic Solution Approaches for Traveling Salesman and Traveling Repairman Problems. IZMIR: Thesis.

Faaeq, M. K., Mat, N. K. N., Faieq, A. K., Rasheed, M. M., & Al-Salami, Q. H. (2018). Towards of smart cities based on the sustainability of digital services. International Journal of Engineering and Technology, 7(4), 436-442.

Hung, C. H. (2016). A Genetic Simplified Swarm Algorithm for Optimizing n-Cities Open Loop Travelling Salesman Problem. Tun Hussein Onn, Malaysia: M.Sc. Faculty of Computer Science and Information Technology University .

Acknowledgment

Use The authors would like to thanks Mustansiriyah university (www.uomustansiriyah.edu.iq) Baghdad – Iraq for its support in the present work.

Jameel, A. M., & Al-Salami, Q. H. (2023). Principal Component Analysis Technique for Finding the Best Applicant for a Job. Cihan University-Erbil Journal of Humanities and Social Sciences, 7(1), 121-125.

Jasim, S. M., & Ali, F. H. (2019). Exact and Local Search Methods for Solving Travelling Salesman Problem with Practical Application. *Iraqi Journal of Science, [S.l], 60*(5), 1138-1153. doi:10.24996/ijs.2019.60.5.22

Nawkhass, M. A., & Birdawod, H. Q. (2017). Transformed and solving multi-objective linear programming problems to single-objective by using correlation technique. *Cihan International Journal of Social Science*, *1*(1), 30-36.

Pham, D. T., Ghanbarzadeh, A., Koc, E., & Otri, S. (2006). The Bee's Algorithm– a Novel Tool for Complex Optimization Problems. *ed(s) 2nd Virtual International Conference on Intelligence Production Machines and Systems* (pp. 454-459). Oxford: Elsevier.

RibeiroKyle, P. F., & Schlansker, S. (2003). *A Hybrid Particle Swarm and Neural Network Approach for Reactive Power Control.* Retrieved from http://engr.calvin.edu/…/Reactivepower-PSO-wks.pdf

Shi, Y. (2004, February). Particle Swarm Optimization. *Electronic Data Systems, Inc. Kokomo, IN 46902, USA Feature Article*.

Shuai, Y., Yunfeng, S., & Kai, Z. (2019). An effective method for solving multiple travelling salesman problem based on NSGA-II. *Systems Science & Control Engineering: an Open Access Journal, 7*(2), 108-116.

Subhi , B., & Ibrahim, M. S. (2018). Solving the Multi-Objective Travelling Salesman Problem with Real Data Application. *Journal of Al-Nahrain University-Science*, 146-161. doi:10.22401/JNUS.21.3.18

Zhiping, D. (2017). Research of improved particle swarm optimization algorithm", . AIP Conference Proceedings 1839, 020148.

Zaidan, M. N., Hamdi, S. S., Birdawod, H. Q., & Agha, A. M. (2024). Factors Influencing Innovation Management in Iraq's Small-and Medium-sized Enterprises. *Cihan University-Erbil Journal of Humanities and Social Sciences*, *8*(1), 126-132.

DOI: http://doi.org/10.24086/icafs2025/paper.1765