

Application of the random key based electromagnetism-like heuristic for solving travelling salesman problems

Gezgin satıcı problemlerinin çözümü için rassal anahtar temelli elektromanyetizma sezgiselinin uygulanması

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Abstract

Among network optimization problems, travelling salesman problem is widely studied one in the literature. Since the problem is computationally hard, many heuristics have been developed to obtain the optimal solution in reasonable time. This paper introduces a hybrid electromagnetism-like heuristics to solve symmetric travelling salesman problems. Originally, electromagnetism-like heuristic is a population based global search algorithm that is inspired by electromagnetism theory in Physics. The proposed mechanism is based on the principle of encouraging randomly generated particles to move toward to optimal solution in the feasible area. In this paper, random-key approach is adapted to electromagnetism-like heuristic to solve vehicle routing problems. Regarding 15 benchmark instances, proposed heuristic procedure produces optimal solutions for small instances. Moreover, as the number of vertices increase in the network, the proposed algorithm generates near optimal solutions. Efficiency of results shows that the proposed algorithm can be evaluated for the solution of combinatorial optimization problems.

Keywords: Electromagnetism-like heuristic, Traveling salesman problems, Uncapacitated vehicle routing

Öz

Ağ optimizasyonu problemleri içerisinde, gezgin satıcı problemi literatürde yaygın bir şekilde çalışılan problemlerden biridir. Problemin hesaplama açısından zor olması dolayısıyla, optimal çözümü elverişli zamanda elde edebilmek için pek çok sezgisel algoritma geliştirilmiştir. Bu çalışma, simetrik gezgin satıcı problemlerinin çözümü için melez bir elektro-manyetizma sezgiseli sunmaktadır. Esasında, elektro-manyetizma sezgiseli, fizikteki elektromanyetizma teorisinden ilham alan, popülasyon tabanlı global bir arama algoritmasıdır. Önerilen mekanizma, fizibil alanda rassal olarak oluşturulan partikülleri optimal çözüme yaklaştırma prensibine dayanır. Bu çalışmada, araç rotalama problemlerini çözebilmek için rassal anahtar yaklaşımı elektromanyetizma sezgiseline adapte edilmiştir. 15 kıyaslama örneği üzerinde test edilen sezgisel yöntem küçük boyuttaki problemler için en iyi çözümleri üretmektedir. Ayrıca, ağdaki nokta sayısı arttıkça, önerilen algoritma optimale yakın çözümler üretmektedir. Sonuçların etkinliği, önerilen algoritmanın kombinatoriyal optimizasyon problemleri çözümü için de değerlendirilebileceğini göstermektedir.

Anahtar kelimeler: Elektromanyetizma sezgiseli. Gezgin satıcı problemi, Kapasite kısıtsız araç rotalama

1 Introduction

The traveling salesman problem (TSP) is an extensively studied classical combinatorial optimization problem that aims to find the optimal tour of n cities by minimizing the total traveling distance, beginning and terminating at the same location and visiting the other locations only one time. Although small instances can be solved for optimality by mixed integer programming, as the size of instances increase the TSP is remarkably challenging. Therefore, academicians published over a thousand articles, developing algorithms and methodologies to solve this problem more effectively [29].

Combinatorial optimization problems involve finding the best possible solution from a finite set of solutions fulfilling certain constraints. Since many combinatorial optimization problems are NP-hard, complete methods- that guaranties optimality- often leads to high computation times for real-world applications [7]. Therefore, approximate methods are utilized to yield acceptable solutions in a significantly reduced computation time by sacrificing the guarantee of finding optimal solution.

The use of meta-heuristics is a rapidly growing field of research, especially for combinatorial optimization problems. Due to the theoretical and practical complexity of the problem,

researchers propose hybrid approaches by integrated meta-heuristics, ie. genetic-tabu search based algorithm [20]; ant colony-tabu search algorithm [18]. The inspiration behind hybridization of different algorithms is to utilize the best performing characteristics of various optimization techniques, that is, integrating these methods are accepted as a good idea [7].

In this study, we represent an adaption of electromagnetism-like (EML) algorithm approach to solve symmetric TSPs. Birbil and Fang [5] introduced EML heuristic for solving global optimization problems. EML heuristic utilizes an attracting-repelling mechanism to converge a solution for optimality. By constructing additional transformation procedures or hybridization with other search and meta-heuristic algorithms, many researchers successfully employed the algorithm for solving discrete and constrained optimization problems. Recently, EML algorithm has been used for computing eigenvalues and eigenvectors [34], redundancy allocation problem [36], prediction of diabetes mellitus [37], vehicle routing [38],[40], cell formation and layout problem [16], maximum betweenness problem [13], nurse scheduling [21], project scheduling [12], single machine scheduling [8]-[10],[30] and set covering problem [23].

The outline of this paper is as follows. In Section 2, a recent literature review on TSPs is presented briefly. In Section 3, the integrated methodology is introduced, underlying methods and their principles are explained in detail. Random key technique and the hybridization with EML algorithm are extensively discussed. In Section 4, computational results are presented. In Section 5, we present the results and our conclusions. Additionally, future research areas are discussed.

2 Traveling salesman problem

Among combinatorial optimization problems, the most prominent problem is generally referred as TSP. It generally intends to discover the optimal route among a given set of locations with beginning and ending at the same predefined location by focusing on the minimum travelling distance.

In this study, we consider a generic un-capacitated vehicle routing problem:

$$\text{Minimize } \sum_i \sum_j d_{ij} X_{ij} \quad (1)$$

$$\sum_j X_{ij} = 1 \quad \forall i \quad (2)$$

$$\sum_i X_{ij} = 1 \quad \forall j \quad (3)$$

$$\sum_{i \in S} \sum_{j \in S, i \neq j} X_{ij} \leq |S| - 1 \quad \forall S \quad (4)$$

$$X_{ij} \in \{0,1\} \quad \forall i \text{ and } \forall j \quad (5)$$

Where X_{ij} is assigned to 1 if truck goes to node j from node i , 0 otherwise. d_{ij} is the distance between node i and node j . Equation (1) is the objective function that minimizes the total routing distance. Equation (2) and Equation (3) ensure only one route between two nodes. Equation (4) is the sub-tour elimination constraint where S is the subset of the cities and the representation of binary decision variables is given in Equation (5).

Researchers develop many approximate methods to resolve TSPs, as: self-organizing maps [3], simulated annealing [15], ant colony [1],[17],[28], tabu search [14],[27], a hybrid simulated annealing-tabu search algorithm [19], genetic algorithm [24], bat algorithm [25] particle swarm optimization [31], blind mole-rat algorithm [39], dynamic multiscale region search algorithm [41]. For further literature review on heuristic algorithms for TSPs, we refer Rego et al. [29]. Authors present an extensive survey for the primary heuristics and the specialized considerations accountable for their effective implementations. Additionally, they presented a computational analysis on the performance of these approaches on diverse set of symmetric and asymmetric TSP benchmark instances.

In recent years, hybridization of different approximate methods is getting more popular in order to effectively solve TSPs. By smart integration of heuristics, authors attempt to promote the advantages and eliminate the shortcomings of algorithms.

3 Proposed algorithm

The electromagnetism-like (EML) heuristic is presented to solve continuous unconstrained optimization problems. In this

study, we integrate random key procedure to EML heuristic in order to solve constrained combinatorial optimization problems. The original EML heuristic can solve effectively test functions such as Rastrigin, Davis, Lavy and Kearfott functions in an appropriate computation time. Thus, we adapt the algorithm by embedding the random key procedure into it to solve sequencing and allocation problems.

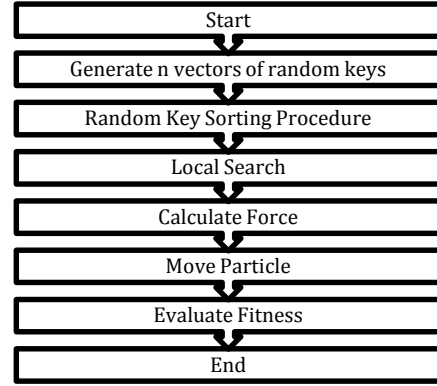


Figure 1: Proposed algorithm.

Figure 1 illustrates the hybrid random key EML heuristic. To represent these kinds of problems with random keys, m position vectors have been generated.

Here, it should be noted that in original EML heuristic, the value of variable k have been the k^{th} ($k \in n$) random coordinate value of the particle i ($i \in m$).

In this modified algorithm, the random numbers, which have been assigned into the cells of the position vector, are the coordinate values and the random key method is applied to the coordinates of particles [37].

3.1 Electromagnetism-Like heuristic

The EML heuristic is inspired from electromagnetism theory and Coulomb law. The algorithm proposes that there is an attracting/repelling effect between particles in the solution space. In elementary physics, it is known that electrically charged particles affect each other with respect to their relative charge magnitude and sign. Hence, two positively or two negatively charged particles repel each other, whereas particles, which have opposite signed charges, attract each other.

In EML algorithm, every particle's charge sign is assumed to be positive and the magnitude of the charge is expressed by its present objective function value. The algorithm implies that if a particle performs better by means of the objective function, it has a greater charge value, and vice versa. The charge of a particle expresses the level of attracting and/or repelling forces in the population. Therefore, highly charged particles attract remaining less charged particles of the population in order to converge to the optimal solution.

A classic population-based search approach proceeds on a set of feasible solutions. Similarly, EML heuristic proposed by Birbil and Fang [5], utilizes an attraction-repulsion mechanism to move these feasible points (solutions) toward optimality. Since EML heuristic works on a set of sample points, the number of particles (points) in the population should be determined. A main assumption is that the particles are uniformly distributed between a corresponding upper bound and a lower bound. The performance of each particle is

evaluated in terms of predetermined objective function $f(x)$. Here, $f(x)$ is a minimization type objective function, m is the size of population and n is the dimension of the problem. The charge of a particle i , q^i , can mathematically be calculated as in Equation (6):

$$q^i = \exp\left(-n \frac{f(x^i) - f(x^{best})}{\sum_{k=1}^m (f(x^k) - f(x^{best}))}\right) \quad (6)$$

Where $f(x^{best})$ is the best level of objective for the current population.

The attracting mechanism encourages the points to move closer to better solutions, and conversely, the repelling mechanism encourages the points by moving away from worse ones [6]. All the particles in the population move along the resultant force that is exerted on them. After calculating the charges of the particles, in order to find to the movement direction of each particle the resultant force vector of each particle is calculated.

The resultant force vector F^i of particle i is computed as in Equation (7).

$$F^i = \sum_{j \neq i}^m \begin{cases} (x^i - x^j) \frac{q^i q^j}{\|x^i - x^j\|^2} & ; f(x^j) < f(x^i) \\ (x^j - x^i) \frac{q^i q^j}{\|x^i - x^j\|^2} & ; otherwise \end{cases} \quad (7)$$

In equation (7), the magnitude of the force which is exerted on particle i emanated from particle j is oppositely proportional to Euclidian distance between these particles. Additionally, the magnitude of force is proportionate to the charges of particles. Hence, higher force occurs between higher charged particles and contrarily lower force occurs between low charged particles. Unlike electrical charges, EML algorithm assigns no signs to the charge of an individual particle.

In order to define the direction of a particular force, algorithm compares the objective function values of particles. The total force vector exerted on each particle F^i is computed by addition of each forces exerted on particle i . Since the direction of total exerted force depends on the location of particles, the particles, that turn out to be sufficiently close, may lead to a direction rather than the statistically projected gradient of f .

In EML algorithm, particles can move on the feasible region to find the optimal solution. This feasible region consists of the area between upper bound (u_k) and lower bound (l_k) of the k variables. RNG vector represents the feasible movements toward the upper bound, or the lower bound, for the corresponding dimension. As the resultant force vector F^i is calculated, each particle moves toward its new position by a random step length λ . Here, λ is generated regarding to standard uniform distribution with parameters $[0,1]$.

$$x^i = x^i + \lambda \frac{F^i}{\|F^i\|} (RNG) \quad i = 1, 2, \dots, m. \quad (8)$$

There exist four procedures in EML algorithm. The initialization phase is the first phase, which is employed for sampling feasible solutions. After calculating the objective values, local neighborhood search procedure start. The local procedure is employed for searching for a better refinement. The third procedure, CalcF, is utilized for calculating the total force exerted on each point, and the last procedure, Move, move a

population of points toward optimality by maintaining feasibility. The pseudo-code of EML is given as follows:

```
Initialize()
i := 1
while i < MAXITER do
Local(LSITER, δ)
F := CalcF()
Move(F)
i := i + 1
endwhile
return result
```

Here, $\delta \in [0,1]$ is the local search parameter, MAXITER corresponds to the maximum iteration number and LSITER corresponds to the maximum local search number and m is the number of sample points (particles) in the search space.

3.2 Random key technique

Random key (RK) approach is firstly introduced by Bean [4] in order to attempt to overcome the difficulty of maintaining feasibility by using real-coded genetic algorithm to address a wide variety of combinatorial optimization problems.

Subsequently, numerous researchers employed this robust concept with different heuristics to find the optimal solution of combinatorial problems, as: Particle swarm algorithm [35] and genetic algorithms [32].

In order to calculate the minimum value of an objective function $f(x)$, an n dimensional position vector should be evaluated. An illustrative example is given as in Table 1 and Table 2:

Table 1: Generation i before RK technique.

1	2	3	4	5	6	7	8	9	10
0.71	0.23	0.83	0.34	0.52	0.04	0.10	0.98	0.64	0.17

Table 2: Generation i after RK technique.

6	7	10	2	4	5	9	1	3	8
0.04	0.10	0.17	0.23	0.34	0.52	0.64	0.71	0.83	0.98

For this example, the elements of the vector are sorted in the ascending order and the random key generator has generated 0.71, 0.23 and 0.83 for the first three elements. Since 0.71 is the 8th largest number of the series, it will be assigned to the 8th element of the vector. Before the transformation, the index of 1 associated to 0.71 will be assigned to the 8th cell of the new vector, simultaneously. The second and third generated random numbers are 0.23 and 0.83. They are respectively the 4th and 9th larger numbers of series. The index of 0.23 is 2 and the index of 0.83 is 3. So, they will be assigned in the 4th and 9th cells of the new cells simultaneously. Thus, the new sequence {6,7,10,2,4,5,9,1,3,8} will be generated.

The steps of random key technique can be summarized as: (i) for each cell of the vector, a random number is generated, (ii) n random numbers are sorted in the ascending order and (iii) the corresponding indices of the random numbers are also sorted with respect to their random number position.

While utilizing the random key technique, a well-performing sorting algorithm is appropriate in terms of time complexity and computational processing speed. After sorting the all the

values, the objective value of the new generation can be calculated.

4 Application

In this section, we investigate the efficiency of proposed algorithm in solving un-capacitated travelling salesman problem.

4.1 Data

The efficiency of the proposed method is discussed on the results of 15-known TSP instances, which can be found in (<http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95>) TSPLIB in the literature. The problem instances and pertinent data is given in Table 3. These test problems are chosen because there was data available in the literature to compare our results with those obtained by other heuristics in the literature.

4.2 Results

We summarized the results in Table 4 to illustrate the individual performance of proposed method.

By performing 35 trials for each problem instance, EML heuristics yield efficient results in small and medium size problems. As the number of vertices increases, the time needed

for solution increases and convergence to optimality decreases. Figure 2 shows the average time needed for finding solution of the problem.

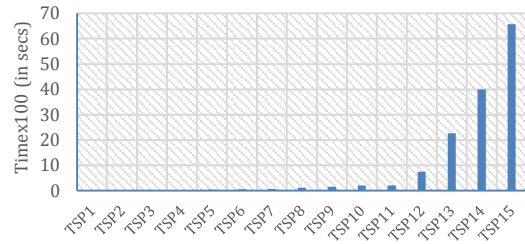


Figure 2: Required time in average for each problem.

4.3 Comparative results

For further investigation of the performance of proposed algorithm in solving TSPs, we compared the results of each problem obtained from 4 heuristic algorithms in the literature. These 15 problem instances in TSP library have been solved by the algorithms of Somhom et al. [33], Aras et al. [2], Cochrane and Beasley [11], Masutti and Castro [22] and proposed EML heuristics. Obtained results are given in Table 5.

Table 3: Data sets.

Dataset ID	Data Set Name	# of vertices	Best known solution
TSP1	eil51	51	426
TSP2	berlin52	52	7542
TSP3	ncit64	64	6400
TSP4	eil76	76	538
TSP5	kroA100	100	21282
TSP6	eil101	101	629
TSP7	lin105	105	14379
TSP8	bier127	127	118282
TSP9	ch130	130	6110
TSP10	ch150	150	6528
TSP11	kroA150	150	26524
TSP12	kroA200	200	29368
TSP13	lin318	318	42029
TSP14	rat575	575	6773
TSP15	rat783	783	8806

Table 4: Analysis of EML algorithm.

Dataset ID	Best with EML Heuristics	Worst with EML Heuristics	Deviation from Best Known (%)
TSP1	428	431	0.469%
TSP2	7542	7748	0.000%
TSP3	6400	6464	0.000%
TSP4	545	560	1.301%
TSP5	21810	22648	2.481%
TSP6	648	662	3.021%
TSP7	14901	15317	3.630%
TSP8	121953	125362	3.104%
TSP9	6435	6546	5.319%
TSP10	6630	7089	1.563%
TSP11	26866	30440	1.289%
TSP12	31216	32687	6.293%
TSP13	42896	45556	2.063%
TSP14	7096	7665	4.769%
TSP15	9354	10675	6.223%

Furthermore, we investigated the effects of parameter setting on computation times. Algorithm utilizes three parameters: these are number of particles m , maximum number of iterations for local search LSITER and maximum number of iterations for local search MAXITER. Figures 3a-3c illustrate the effects of these parameters on computation times. Parameter setting in this study is done by several random trials. We have done our computations with 2.20 GHz and 2.0 GB RAM computer. The procedure is coded in Microsoft® Visual Basic® for Applications.

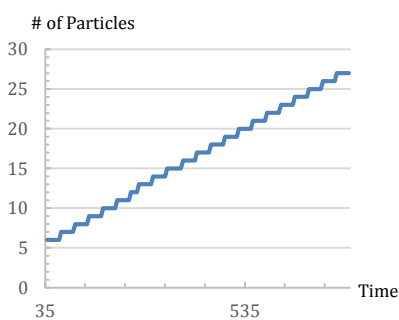
5 Conclusions and discussions

For improving valuable standards for the advancement of hybrid meta-heuristics, it will be important to enhance current approaches on algorithm development [7].

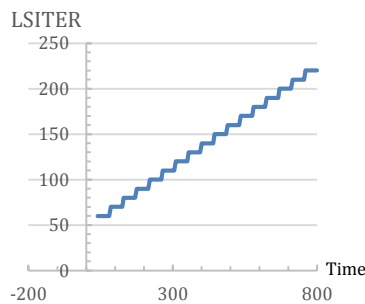
In this paper, we developed a hybrid procedure to solve uncapacitated TSPs. The proposed method has two phases. In the first phase, we proposed a procedure to initialize random solutions by excluding the problem constraints. Next, we utilized EML heuristics to improve the quality of obtained solution. We tested it on a set of TSP instances. The accuracy of results shows the algorithm performs well in terms of optimality. However, an extra effort is required to improve the computational time. We believe that modifying the code syntax or replacing the programming language with another programming language will yield efficient results in a reasonable computation time, especially for the problems that has higher dimensions.

Table 5: Comparative analysis of EML algorithm.

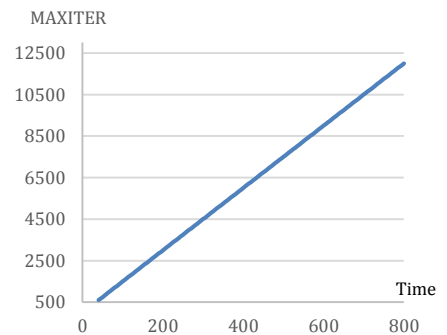
ID	Best Known	Somhom et al. [32]			Aras et al. [2]			Cochrane and Beasley [11]			Masutti and Castro [22]			Proposed Method		
		Mean	SD	Best	Mean	SD	Best	Mean	SD	Best	Mean	SD	Best	Mean	SD	Best
TSP1	426	442.9	4.59	432	440.57	3.44	433	438.7	3.52	429	437.47	4.2	427	432.735	3.92	428
TSP2	7542	8363.7	241.82	7778	8025.07	248.79	7715	8073.97	270.14	7716	7932.5	277.25	7542	7737.25	259.66	7542
TSP3	6400	6594.07	72.97	6482	6547.6	66.02	6482	6400	0	6400	6400	0	6400	6423	33.69	6400
TSP4	538	563.2	6.45	554	562.27	5.23	552	556.1	8.03	542	556.33	5.3	541	550.70806	6.38	545.086
TSP5	21282	24678.8	862.09	23009	21616.77	164.21	21410	21868.47	245.76	21369	21522.73	93.34	21333	21666.264	161.66	21809.8
TSP6	629	665.93	7.27	655	655.57	5.95	640	654.83	6.57	641	648.63	3.85	638	648.50838	5.91	648.387
TSP7	14379	16111.37	609.1	14999	14475.6	118.24	14379	14702.23	328.37	14379	14400.17	44.03	14379	14650.344	274.935	14900.5
TSP8	118282	128920.3	6563.13	120110	121733.3	1240.04	119840	121780.3	1564.02	118760	120886.3	1158.79	118970	121419.55	1231.495	121953
TSP9	6110	6416.8	92.97	6265	6307.23	62.95	6203	6291.77	64.98	6142	6282.4	60.15	6145	6358.6829	65.2625	6434.97
TSP10	6528	6842.8	105.97	6634	6751	62.18	6631	6753.2	83.01	6629	6738.37	76.14	6602	6684.185	77.825	6630
TSP11	26524	29960.9	564.39	28948	27401.33	252.03	26930	27346.43	223.31	26932	27355.97	327.91	26678	27907	321.91	26866
TSP12	29368	33228.33	638.63	31669	30415.67	132.86	30144	30257.53	342.98	29594	30190.27	273.38	29600	31442.493	276.9625	31216
TSP13	42029	45832.83	541.67	44869	43922.9	382.29	43154	43704.97	391.48	42975	43696.87	410.06	42834	43882.5	411.375	42896
TSP14	6773	8301.83	106.88	8107	7173.63	39.47	7090	7125.07	40.91	7039	7115.67	37.47	7047	7601.5	37.1825	7096
TSP15	8806	10721.6	108.81	10532	9387.57	39.44	9316	9326.3	48.45	9185	9343.77	46.97	9246	9943	48.9175	9354



(a): Effect of number of particles m .



(b): Effect of *LSITER*.



(b): Effect of *MAXITER*.

Figure 3: The effect of parameters on computation time.

Additionally, the parameter setting in the two-phase EML algorithm has significant effect on the results and computation time, directly. If the parameter of m (which denotes the number of particles) increases sufficiently, local search procedure ensures to converge or to find the optimal objective solution. However, simultaneously, this situation increases computation time too much and it decreases the practicality of the algorithm. Hence, parameter setting is crucial for the algorithm's performance.

Instead of local search procedure in the proposed method, simulated annealing algorithm can be utilized to increase the convergence to optimal objective solution. This hybrid approach will be explored in order to decrease the total computation time.

For future research, the proposed algorithm can be utilized to solve other combinatorial optimization problems. Additionally, multiple objective extensions of the algorithm and extensions handling uncertainty in the problem statement are other interesting topics in order to develop new heuristic algorithms especially for vehicle routing problems.

6 References

- [1] Abd Aziz Z. "Ant colony hyper-heuristics for travelling salesman problem". *Procedia Computer Science*, 76, 534-538, 2015.
- [2] Aras N, Altinel KI, Oommen J. "A kohonen-like decomposition method for the traveling salesman problem: KNIESDECOMPOSE". *14th European Conference on Artificial Intelligence (ECAI)*, Berlin, Germany, 20-25 August 2000.
- [3] Angeniol B, Vaubois GDLC, Texier JYL. "Self-organizing feature maps and the traveling salesman problem". *Neural Networks*, 1(4), 289-293, 1988
- [4] Bean JC. "Genetic algorithms and random keys for sequencing and optimization". *ORSA Journal on Computing*, 6(2), 154-160, 1994.
- [5] Birbil Sİ, Fang SC. "An electromagnetism-like mechanism for global optimization". *Journal of Global Optimization*, 25(3), 263-282, 2003.
- [6] Birbil Sİ, Fang SC, Sheu RL. "On the convergence of a population-based global optimization algorithm". *Journal of Global Optimization*, 30(2-3), 301-318, 2004.
- [7] Blum C, Puchinger J, Raidl GR, Roli A. "Hybrid metaheuristics in combinatorial optimization: A survey". *Applied Soft Computing*, 11(6), 4135-4151, 2011.
- [8] Chang PC, Chen SH, Fan CY. "A hybrid electromagnetism-like algorithm for single machine scheduling problem". *Expert Systems with Applications*, 36, 1259-1267, 2009.
- [9] Chao CW, Liao CJ. "A discrete electromagnetism-like mechanism for single machine total weighted tardiness problem with sequence-dependent setup times". *Applied Soft Computing*, 12, 3079-3087, 2012.
- [10] Chen SH, Chang PC, Chan CL, Mani V. "A hybrid electromagnetism like algorithm for the single machine-scheduling problem". *Lecture notes in Computer Sciences*, 4682, 543-552, 2007.
- [11] Cochrane EM, Aras N. "The co-adaptive neural network approach to the euclidean travelling salesman problem". *Neural Networks* 16(10), 1499-525, 2004.
- [12] Debels D, Vanhoucke M. "The electromagnetism meta-heuristic applied to the resource-constrained project-scheduling problem". *Lecture Notes in Computer Science*, 3871, 259-270, 2006.
- [13] Filipovic V, Kartelj A, Matic D. "An electromagnetism metaheuristic for solving the maximum betweenness Problem". *Applied Soft Computing*, 13, 1303-1313, 2013.
- [14] Gendreau M, Laporte G, Semet F. "A tabu search heuristic for the undirected selective travelling salesman problem", *European Journal of Operational Research*, 106, 539-545, 1998.
- [15] Geng X, Chen Z, Yang W, Zhao, K. "Solving the traveling salesman problem based on an adaptive simulated annealing algorithm with greedy search". *Applied Soft Computing*, 11, 3680-3689, 2011.
- [16] Jolai F, Tavakkoli-Moghaddam R, Golmohammadi A, Javadi B. "An Electromagnetism-like algorithm for cell formation and layout problem". *Expert Systems with Applications*, 39, 2172-2182, 2012.
- [17] Jun-Man K, Yi Z. "Application of an Improved Ant Colony Optimization on Generalized Traveling Salesman Problem". *Expert Systems with Applications*, 17, 319-325, 2012.
- [18] Lin Y, Yeh CH, Huang PS. "A hybrid ant-tabu algorithm for solving a multistate flow network reliability maximization problem". *Applied Soft Computing*, 13(8), 3529-3543, 2013.
- [19] Lin Y, Bian Z, Liu X. "Developing a dynamic neighborhood structure for an adaptive hybrid simulated annealing-tabu search algorithm to solve the symmetrical traveling salesman problem". *Applied Soft Computing*, 49, 937-952, 2016.
- [20] Mantawy AH, Abdel-Magid YL, Selim SZ. "A new genetic-based tabu search algorithm for unit commitment problem". *Electric Power Systems Research*, 49(2), 71-78, 1999.
- [21] Maenhout B, Vanhoucke M. "An electromagnetic meta-heuristic for the nurse-scheduling problem". *Journal of Heuristics*, 13, 359-385, 2007.
- [22] Masutti TAS, Castro LND. "A self-organizing neural network using ideas from the immune system to solve the traveling salesman problem". *Information Sciences*, 179(10), 1454-1468, 2009
- [23] Naji-Azimi Z, Toth P, Galli L. "An electromagnetism metaheuristic for the unicost set covering problem". *European Journal of Operational Research*, 205, 290-300, 2010.
- [24] Nagata Y, Soler D. "A new genetic algorithm for the asymmetric traveling salesman problem". *Expert Systems with Applications*, 39, 8947-8953, 2012.
- [25] Osaba E, Yang XS, Diaz F, Lopez-Garcia P, Carballedo R. "An improved discrete bat algorithm for symmetric and asymmetric traveling salesman problems". *Engineering Applications of Artificial Intelligence*, 48, 59-71, 2016.
- [26] Pasti R, Castro LND. "A neuro-immune network for solving the traveling salesman problem". *International Joint Conference on Neural Networks*, Vancouver, Canada, 16-21 July 2006.
- [27] Pedro O, Saldanha R. "A Tabu Search Approach for the Prize Collecting Traveling Salesman Problem". *Electronic Notes in Discrete Mathematics*, 41, 261-268, 2013.

- [28] Ramtaka D, Kumar S, Patle VK. "Route Optimization by Ant Colony Optimization Technique". *Procedia Computer Science*, 92, 48-55, 2016.
- [29] Rego C, Gamboa D, Glover F, Osterman, C. "Traveling salesman problem heuristics: Leading methods, implementations and latest advances". *European Journal of Operational Research*, 211, 3, 2011, 427-441, 2011.
- [30] Sels V, Vanhoucke M. "A hybrid Electromagnetism-like Mechanism/tabu search procedure for the single machine-scheduling problem with a maximum lateness objective". *Computers and Industrial Engineering*, 67, 44-55, 2010.
- [31] Shi XH, Liang YC, Lee HP, Lu C, Wang QX. "Particle swarm optimization-based algorithms for TSP and generalized TSP". *Information Processing Letters*, 103, 169-176, 2007.
- [32] Snyder LV, Daskin MS. "A random-key genetic algorithm for the generalized traveling salesman problem". *European Journal of Operational Research*, 174(1) 38-53, 2006.
- [33] Somhom S, Modares A, Enkawa T. "A self-organizing model for the traveling salesman problem". *Journal of the Operational Research Society*, 48(4-6), 919-928, 1997.
- [34] Taheri SH, Ghazvini H, Saberi-Nadjafi J, Biazar J. "A hybrid of the restarted Arnoldi and electromagnetism meta-heuristic methods for calculating eigenvalues and eigenvectors of a non-symmetric matrix". *Applied Mathematics and Computation*, 191, 79-88, 2007.
- [35] Tasgetiren MF, Sevkli M, Liang YC, Gencyilmaz G. "Particle swarm optimization algorithm for makespan and total flowtime minimization in permutation flowshop sequencing problem". *European Journal of Operational Research*, 177(3), 1930-1947, 2007.
- [36] Teimouri M, Zaretalab A, Niaki STA, Mani Sharifi M. "An efficient memory-based electromagnetism-like mechanism for the redundancy allocation problem". *Applied Soft Computing*, 38, 423-436, 2016.
- [37] Wang KJ, Adrian AM, Chen KH, Wang KM. "An improved electromagnetism-like mechanism algorithm and its application to the prediction of diabetes mellitus". *Journal of Biomedical Informatics*, 54, 220-229, 2015.
- [38] Wu P, Yang KJ, Huang BY. "A revised EM-like mechanism for solving the vehicle routing problems". *2nd International Conference on Innovative Computing, Information and Control 2007-ICICIC '07 Proceedings 181*, Kumamoto, 5-7 September 2007.
- [39] Yıldırım T, Kalaycı CB, Mutlu Ö. "A novel metaheuristic for traveling salesman problem: blind mole-rat algorithm". *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 22(1), 2016, 67-70.
- [40] Yurtkuran A, Emel E. "A new hybrid electromagnetism-like algorithm for capacitated vehicle routing problems". *Expert Systems with Applications*, 37, 3427-3433, 2010.
- [41] Zhang H, Zhou J. "Dynamic multiscale region search algorithm using vitality selection for traveling salesman problem". *Expert Systems with Applications*, 60, 81-95, 2016.