An Improved Electromagnetism-like mechanism for Capacitated vehicle routing problem

Akram Zarei
Artificial Intelligent Student
Mashad Branch, Islamic Azad University, Mashad, Iran
Zarei353@yahoo.com

Mohammad-R. Akbarzadeh-T.
Center of Excellence on Soft Computing and Intelligent Information Processing
Ferdowsi University of Mashhad
Akbarzadeh@ieee.org

Masoud Gharehjanloo
Department of Computer Engineering
Minoodasht Branch, Islamic Azad University, Minoodasht, Iran
Gharehjanloo@iauminoodasht.ac.ir

***Abstract*— In this paper a new electromagnetism-like mechanism is proposed for combinatorial optimization of capacitated vehicle routing problem. electromagnetism-like mechanism is a new metaheuristic method and inspired by the attraction and repulsion mechanism of the electromagnetism theory. we propose a new electromagnetism-like mechanism that it includes a new distance measure between solutions and new effective process of attraction and repulsion. In order to analyze the proposed algorithm a comparison is done with existing algorithm for this problem. Computational results show that the proposed electromagnetism-like mechanism algorithm has a good performance for the considered problem.**

Keywords- Electromagnetism-like mechanism; capacitated vehicle routing; Electromagnetism theory; Meta-heuristics

I. Introduction

Since good distribution takes almost 20% of total production cost, improving efficiency in good transportation can lead to greater saving in the cost and higher competition in regional economy. Most of the problems in distributing goods can be considered as vehicle routing problem (VRP), which is one the most important issues in combinatorial optimization with numerous industrial applications. This paper is devoted to analyzing of capacitated vehicle routing problem (CVRP), which serves as an extension of VRPs. The CVRP is formally defined as an undirected graph $G = (V, E)$ where $V = \{v_0, v_1, \dots, v_n\}$ is a vertex set and $E = \{(v_i, v_j) | v_i, v_j \in V, i < j\}$ is an edge set. In this problem there is only one depot, which is represented by vertex zero. Also, this problem has m vehicles with capacity of Q to response demands of q_i from n customers. Each customer v_i has a service time t_i. A non-negative cost (distance or travel time) matrix $C = (c_{ij})$ between customers v_i and v_j is defined on edge E. One solution include a set of routes $R_i = \{v_{i0}, v_{i1}, \dots, v_{ik+1}\}$ in which $v_{ij} \in V$ and $v_{i0} = v_{ik+1} = 0$ and each route satisfy the condition $\sum_{v_{ij} \in R_i} q_j \leq Q$. Cost of the problem solution is sum of the costs of its routes R_i, defined as follows:

$$\mathrm{Cost} = \sum_{i=1}^{m} \mathrm{Cost}(R_i) = \sum_{j=0}^{k} c_{j,j+1} + \sum_{j=0}^{n} t_j \tag{1}$$

CVRP includes identifying a set of maximum of m routes of minimum total cost, such that each route both starts from and ends in depot, each customer is visited exactly once by exactly one vehicle and in each route total of customers demand do not exceed Q.

There are extensive studies on algorithms for solving VRPs. Since VRP is NP-hard, exact algorithms are only available for those problems with small size. In the last several decades, researchers mainly focused on heuristics and metaheuristic methods, which can find quite good solutions within rational time, especially for real life applications. As examples of works done that used metaheuristic methods we can mention simulated annealing [1], genetic algorithm [2,3], tabu search [4,5], ant colony [6] and particle swarm optimization [7]. These methods of metaheuristic usually take advantage of other methods such as 2-opt or 3-opt or local search methods to improve quality of solutions.

Electromagnetism-like mechanism (EM) proposed by Fang and Birbil [8] is a new metaheuristic method based on principle of attraction or repulsion for each particle during the search. EM has been used successfully for optimizing continuous and discreet problems. Yang and his colleagues [9] were the first to use EM for training neural network with great saving on the computation memories and time, and the results indicate that EM performed much better than the genetic algorithm in finding the global optimum. The other advantage and interesting factors of EM is that, it needs few parameters to be set and this could be one of the greatest advantages of any algorithm.

EM for CVRP is used in [10] and [11]. In [10], they solve the problem by combining EM and Iterated Swap Procedure, which is a local search. Also, they used Random-Key Procedure (RKP) integrated into EM to solve CVRP. Real-coded position vectors are decoded by RKP to show corresponding set of routes. In this kind of answers, routes are not clear and we have an order of customers.

In this paper, much effort is put to improve the EM and apply that to CVRP. The proposed EM in this paper is using suitable encoding and initial population and includes two new and important features. First is a new distance measure between two particles and second is the effective attraction and repulsion operators, which in turn locate the particle better and provide answers with high quality in problem space. Also, the proposed EM algorithm, instead of considering all the forces particles apply to a particle, just take the most effective particle and this reduce the computation effort.

In continue, in section II and III we introduce the background of EM and the structure of the proposed EM algorithm. In section IV calculation results are given and finally, conclusions are included in the last section.

II. INTRODUCING EM THEORY

EM is inspired by the attraction and repulsion mechanism of the electromagnetism theory [8]. In EM each particle is considered a solution in a D dimensional space and its search direction is set according to other particles force. The principal fact in EM improvement is that better solutions attract other solutions to their direction and also they are precluded from moving in the direction of wrong solutions, the former is called attraction and the latter is called repulsion. Each particle of X_i^t has electrical charge that is like the following:

$$q_i^t = \exp\left\{-D\frac{f(X_i^t) - f(X_{best}^t)}{\sum_{k=1}^{N_p}(f(X_k^t) - f(X_{best}^t))}\right\} \quad (2)$$

q_i^t is the charge of particle i in iteration t. $f(X_i^t)$ and $f(X_{best}^t)$ represent the objective function value of the particle i and the best objective function value obtained from the population at iteration t, respectively. For searching the optimum solution, particle i defined its search direction according to the following total force:

$$F_i^t = \sum_{j\neq i}^{N_p}\begin{cases}(X_j^t - X_i^t)\dfrac{q_i^t q_j^t}{\|X_j^t - X_i^t\|^2} & \text{if } f(X_j^t) < f(X_i^t)\\[2ex] (X_i^t - X_j^t)\dfrac{q_i^t q_j^t}{\|X_j^t - X_i^t\|^2} & \text{if } f(X_j^t) \geq f(X_i^t)\end{cases} \quad (3)$$

$q_i^t q_j^t$ is the product of the charges of particles i and j. While $\|X_j^t - X_i^t\|^2$ is the square of distance between i and j. If particle j is better than particle i, $f(X_j^t) < f(X_i^t)$ the force is positive and particle j is attracting particle i. Otherwise, the force is negative and repulsion is applied on i. After applying forces each particle according to (4) is moved to its new location.

$$X_i^{t+1} \leftarrow X_i^t + \lambda\frac{F_i^t}{\|F_i^t\|}(RNG) \quad (4)$$

λ is a random number in range of [0,1] and RNG is an allowed feasible range.

III. PROPOSED EM ALGORITHM

In this section the proposed EM algorithm is used for solving the CVRP and its different steps is explained. The mentioned algorithm contains several features such as: a new distance measure between two particles and the effective attraction and repulsion operators for moving the particle to its new location.

A. *Particle encoding and initial population generation*

How to code a particle has major effect on algorithm execution time, convergence speed and efficiency of algorithm. Therefore, modeling of particle is done in a way that has the minimum overload. A model of this encoding is shown in Fig. 1 (with 10 customers and 3 vehicles). Each of the solutions' block shows one customer and value zero shows depot, each two consecutive block shows an edge that shows how the routes are travelled [12].

0	3	5	8	1	0	2	9	6	0	4	7	10	0

Figure 1. particle encoding.

The algorithm considered for the initial population, is enjoying objectiveness and great diversity that leads to search all over the problem space. This algorithm works in a way that at the beginning several nodes (customers) are chosen as seeds so the routes are made according to these seeds. Seeds are chosen in a way that they are the furthest nodes from the depot. Number of these routes (seeds) is chosen manually and by a parameter that could be set. After seeds are chosen, the remaining customers should be put on the routes. For this reason, cost of a customer for all the feasible places is calculated and then a location with the minimum cost is chosen. It worth mentioning that feasibility of each route is always considered.

B. *charge Calculation*

In EM algorithm, the charge represents the quality of the solution. If the objective value of particle i is closer to the best objective value, the charge of particle i will be higher. For calculating the charge (5) is used:

$$q_i^t = \exp\left(-\frac{f(X_i^t) - f(X_{best}^t)}{f(X_{worst}^t) - f(X_{best}^t)}\right) \quad (5)$$

$f(X_{best}^t)$ and $f(X_{worst}^t)$ are the best and worst objective values that are obtained from existing particles in population in iteration t. $f(X_i^t)$ is the value of objective function of i.

C. *Force Calculation*

1) *Distance measure between particles*

Before calculating the force of a particle, it is necessary to design a new distance measure between customer sequence for the CVRP. n_d is the number of edges that are similar on the two considered particles. For getting the distance between particles, (n_d) is subtracted from number of edges (n).

Higher value of n_d implies that the two particles are more similar to each other, while lower value shows greater difference. Therefore $n - n_d$ is used as the discrete distance between particles.

2) Particle Force

Forces applied on particle i by the particles in the population is calculated by (6):

$$F_{ij}^t = \begin{cases} \dfrac{q_i^t q_j^t}{(n-n_d)^2} & \text{if } f(X_j^t) < f(X_i^t) \\ -\dfrac{q_i^t q_j^t}{(n-n_d)^2} & \text{otherwise} \end{cases} \quad j = 1, \dots, N_p \;\; i \neq j \qquad (6)$$

$q_i^t q_j^t$ is the product of charge of particles i and j. $(n - n_d)^2$ is the square of distance between particles i and j.

D. Movement

One of the most important factors in successful using of EM is that how a particle is moving to a new location. In basic EM algorithm, as shown in (4), with summation of forces applied on one particle, and with random step length, the particle is moving to a new location. In this paper a new mechanism for attraction and repulsion is presented that is used for CVRP that is explained later.

1) The Attraction operator

If the incoming force from particle j to particle i is greater than zero $\left(F_{ij}^t \geq 0\right)$ then particle j is applying attracting force to the particle i. It implies that the elements of particle i should contain some elements of particle j. At first, common edges between i and j are found and then they are moved without any change to next generation $i + 1$. Considering Fig. 2 similar edges between i and j are passed to the next generation but not all the customers are serviced. For adding the remaining customers (the removed edges), with the help of proposed algorithm the initial population is generated in a way that cost for all the feasible location is calculated and then the location with minimum cost is chosen. Feasibility of each route is also checked i.e. if the vehicle is full a new route is added.

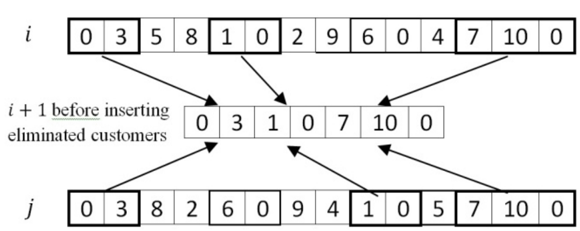

Figure 2. Attraction operator.

2) The repulsion operator

If the incoming force from particle j to the particle i is smaller than zero ($F_{ij}^t \leq 0$) particle j exerts a repulsion force on particle i. It implies that particle i is different from particle j as much as possible. This process is working opposite to the attraction in a way that common edges between i and j are removed and the rest of edges are moved to the next generation (see Fig. 3.). Same as attraction process, removed customers will be placed in a location with minimum cost and new solution would be made.

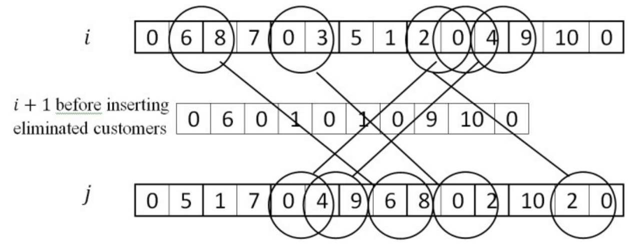

Figure 3. Repulsion operator.

E. Movement Method

In the proposed algorithm each particle generate its own new string according to incoming forces from other particles using (7):

$$X_i^t = \begin{cases} X_i^t \otimes X_j^t & \text{if } F_{ij}^t \geq 0 \\ X_i^t \odot X_j^t & \text{otherwise} \end{cases} \quad j = 1,2, \dots, N_p, \quad i \neq j \qquad (7)$$

in which $\otimes$ shows attraction and $\odot$ shows repulsion. Basically, according to EM algorithm particle of X_i^t is moved because of forces applied to X_i^t by other particles in population. All the particles in the population $(X_i^t\, j = 1, \dots, N_p,\;\; i \neq j)$ should individually exert either attraction or repulsion forces on X_i^t therefore it needs higher calculation time. For reducing the calculation effect, a particle j^* is chosen that has the maximum (or minimum) force on particle i and then this particle is moved only because of j^* forces to its new location. j^* is defined according to equation (8):

$$j^* = \begin{cases} \arg \max\limits_{j=1,2,\dots,N_p} \left\{\left|F_{ij}^t\right|\right\} & \text{if } r \leq r_0 \\ \arg \min\limits_{j=1,2,\dots,N_p} \left\{\left|F_{ij}^t\right|\right\} & \text{otherwise} \end{cases} \qquad (8)$$

$\left|F_{ij}^t\right|$ is the absolute value of F_{ij}^t, r is a random number between [0,1] and r_0 is a parameter for exploiting the maximum force against the minimum force.

IV. Computational Experiments

The proposed algorithm is tested on a set of data suggested by Christofides [13], which include 14 instances. We have to note that the available customers between C and C10 are distributed randomly while customers between C11 to C14 are distributed in a cluster manner.

For determining suitable values for the proposed algorithm an initial test was done. Range of parameter values for population number is $N_p = [40,100]$, $r_0 = (0.7,1)$ and maximum iteration is 800. Proposed EM algorithm is done 20 times for every instance and the best result is reported in table I. As mentioned in table proposed EM algorithm gives better solutions comparing basic EM algorithm and proposed hybrid EM algorithm in [10], which is mixed with a local search (HEMA). Considering problem encoding and generated initial population in this paper that give better answers comparing to random population, convergence time is also reduced and it will reach the answer in less number of iteration. Also, because of considering just one force, instead of all the particles forces, exerted on the particle, computation effort is reduced. The numbers that have (*) are the results as the best-known solutions.

TABLE I. COMPARISON OF METHOD IN [10] AND PROPOSED EM

Problem	EMA	HEMA	Proposed EM
	Best	*Best*	*Best*
C1	524.61	524.61	524.61*
C2	901.23	849.77	836.16
C3	899.49	844.72	827.48
C4	1101.23	1059.03	1029.59
C5	1401.42	1302.33	1299.83
C6	571.88	555.43	555.43*
C7	950.33	909.68	909.68*
C8	891.94	866.32	865.94*
C9	1201.30	1181.60	1163.69
C10	1501.32	1417.88	1395.85*
C11	1102.39	1042.11	1042.11*
C12	851.24	847.56	820.93
C13	1619.40	1542.86	1541.14*
C14	873.64	866.37	866.37*

Also, proposed method is compared with seven other papers that exploit metaheuristic methods for CVRP. Deviation measure percentage between the best-generated solution by any method and the best solution for the reported instance is calculated with the following:

$$\mathrm{PD} = \left[\frac{\mathrm{sol} - \mathrm{BSF}}{\mathrm{BSF}}\right] \times 100\% \qquad (9)$$

The results are given in table 3. Value zero shows that relevant algorithm for that instance found the best answer. Selected algorithms include Tabu search (TS-OSM)[4], Simulated annealing (SA-OSM)[1], Genetic algorithm (GA)[2,3](GA-P and B&A), Ant Colony algorithm (ACO-Y)[6] and particle group improvement algorithm (PSO-A&K)[7]. The final line (APD) is showing the average deviation. The proposed algorithm reached the second least standard deviation.

V. CONCLUSION

In this article, a new EM algorithm for CVRP is proposed. This algorithm is designed in a way that searches the problem space and finds the optimum solution. One of the important factors in successfully using this algorithm is that how a particle is moving to a new location in the problem.

Here, an effective attraction and repulsion process is proposed that performs good search of problem space and moves toward the optimum solution. The proposed algorithm has little parameters to set and it is easy to implement. Calculation results show the superiority of this algorithm to basic EM and some of the metaheuristic used for CVRP. This algorithm is quite competitive with other existing algorithm. It worth mentioning that this algorithm is flexible and could be used for combined optimization problems.

REFERENCES

[1] Osman, I. H. ,” Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem,” Operations Research, 41, 421–451, 1993.

[2] Prins, C. ,“ A simple and effective evolutionary algorithm for the vehicle routing problem,” Computers & Operations Research, 31, 2004.

[3] Baker, B. M., & Ayechew, M. A. ,” A genetic algorithm for the vehicle routing problem,” Computer and Operational Research, 7, 301–317, 2003.

[4] Osman, I. H. ,” Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem,” Operations Research, 41, 421–451, 1993.

[5] Gendreau, M., Laporte, G., Musaraganyi, C., & Taillard, E. D,” A tabu search heuristic for the heterogeneous fleet vehicle routing problem,” Computers & Operations Research, 41, 421–451, 1999.

[6] Yu, B., Yang, Z.-Z., & Yao, B. ,” An improved ant colony optimization for vehicle routing problem,” European Journal of Operational Research, 196(1), 171–176, 2008.

TABLE II. COMPUTATIONAL RESULTS OF CHRISTOfiDES BENCHMARKING PROBLEMS.

Prob.	TS-OSM	SA-OSM	GA-B&A	GA-P	PSO-A&K	ACO-Y	Proposed EM
C1	0.00	0.64	0.03	0.00	0.00	0.00	0.00
C2	1.04	0.32	1.73	0.00	1.09	0.00	0.90
C3	1.07	0.34	1.76	0.00	0.39	0.46	1.34
C4	2.29	2.87	2.66	0.19	1.99	0.00	1.17
C5	4.85	6.56	6.77	0.39	2.52	1.09	0.84
C6	0.00	0.00	0.87	0.00	0.00	0.00	0.00
C7	0.36	0.00	0.48	0.00	0.87	0.00	0.00
C8	0.00	0.00	0.79	0.00	0.12	0.00	0.00
C9	2.18	0.12	2.62	0.00	1.59	0.00	1.14
C10	1.87	1.58	6.24	0.49	2.33	0.00	0.00
C11	0.00	12.84	1.73	0.00	0.93	0.00	0.00
C12	0.00	0.78	7.10	0.00	0.00	0.00	1.37
C13	0.38	0.25	1.36	0.11	0.32	0.31	0.00
C14	0.00	2.72	0.68	0.00	0.00	0.00	0.00
APD	1.00	2.07	2.49	0.85	0.87	0.13	0.46

[7] Ai, T. J., & Kachitvichyanukul, V. ,” A particle swarm optimization for the capacitated vehicle routing problem,” International Journal of Logistics and SCM Systems, 2, 50–55, 2007.

[8] S.I. Birbil, S.C. Fang," An electromagnetism-like mechanism for global optimization," Journal of Global Optimization 25, 263-282, 2003.

[9] Yang, W. H., "A Study on the Intelligent Neural Network Training Using the Electromagnetism Algorithm," Unpublished Master Thesis, I-Shou University, Kaohsiung County, Taiwan, 2002.

[10] Alkın Yurtkuran, Erdal Emel , " A new Hybrid Electromagnetism-like Algorithm for capacitated vehicle routing problems," Expert Systems with Applications 37 (2010) 3427–3433.

[11] Peitsang Wu , Kung-Jiuan Yang and Bau-Yuan Huang ," A Revised EM-like Mechanism for Solving the Vehicle Routing Problems," 0-7695-2882-1/07 $25.00 ©2007 IEEE

[12] Panagiotis P. Repoussis, Christos D. Tarantilis, and George Ioannou," Arc-Guided Evolutionary Algorithm for the VehicleRouting Problem with Time Windows," IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, VOL. 13, NO. 3, JUNE 2009.

[13] Christofides, N., & Eilon, S," An algorithm for the vehicle dispatching problem," Operational Research Quarterly, 20, 309–318, 1969.