Solution for Fuzzy Road Transport Traveling Salesman Problem Using Eugenic Bacterial Memetic Algorithm

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Abstract*— The aim of the Traveling Salesman Problem (TSP) is to find the cheapest way of visiting all elements in a given set of cities and returning to the starting point. In solutions presented in the literature costs of travel between nodes (cities) are based on Euclidean distances, the problem is symmetric and the costs are constant. In this paper a novel construction and formulation of the TSP is presented in which the requirements and features of practical application in road transportation and supply chains are taken into consideration. Computational results are presented as well.*

Keywords— Traveling Salesman Problem, time dependent fuzzy costs, eugenic bacterial memetic algorithm

1 Introduction

The aim of the Traveling Salesman Problem (TSP) is to find the cheapest way of visiting all elements in a given set of cities where the cost of travel between each pair of them is given, including the return to the starting point. The TSP is a very good representative of a larger class of problems known as combinatorial optimization problems. If an efficient algorithm (i.e., an algorithm that will guarantee to find the optimal solution in polynomial number of steps) can be found for the traveling salesman problem, then efficient algorithms could be established for all other problems in the NP (nondeterministic polynomial time) class, thus TSP belongs to the so called NP-hard complexity class. TSP is a well studied NP-hard problem [5]. An algorithm can be considered as an effective (good) one if it has a polynomial function of the problem size n, that is, for large values of n, the algorithm runs in time at most Kn^c for some constant number K and c. The question whether or not there is a good algorithm for the TSP has not been settled. For its practical importance and wide range of application in practice [5] many approaches, heuristic searches and algorithms have been suggested [8, 10, 11, 12], while different extensions and variations of the original TSP have been investigated [6, 9, 13].

Solutions presented in the literature most frequently have the following features. Costs of travel between nodes (cities) are based on Euclidean distances, the problem is symmetric, meaning that the cost from $node_i$ to $node_j$ equals to the cost from $node_j$ to $node_i$, and the costs are constant. In this paper a novel construction and formulation of the TSP is presented in which the requirements and features of practical application in road transportation and supply chains are taken into consideration. Since the original formulation of the problem states: the aim is to find the "cheapest" tour, thus the cost matrix that represents the distances between each pair must be determined by calculating the actual costs of transportation processes. The costs of transportation consist of two main elements: costs proportional to transit distances (km) and costs proportional to transit times. Obviously the physical distances can be considered as constant values in a given relation, but transit times are subject to external factors, such as weather conditions, traffic circumstances, etc., so they should be treated as a time-dependent variable. Furthermore the actual costs are rarely constant and predictable, so fuzzy cost coefficient can be applied in order to represent the uncertainty [15, 17]. On the other hand in real road networks the actual distance between two points often alter from the Euclidean distance, furthermore occasionally some extra costs (e.g., ferriage, tunnel fare) can modify the distance-related variable costs. Considering these characteristics the original TSP should be reconstructed, so that realistic solutions can be developed.

For solving the above-mentioned fuzzy road-transport TSP (FRTTSP) in this paper we suggest a eugenic bacterial memetic algorithm (EBMA) since that algorithm is suitable for global optimization of even non-linear, high-dimensional, multi-modal, and discontinuous problems. As numerical example a modified TSP (FRTTSP) instance is considered, in which the elements of cost matrix are dependent on the steps they are selected to carry on with.

2 Formulating and solutions for the classical TSP

In the case of the traveling salesman problem, the mathematical description can be a graph where each city is denoted by a point (or node) and lines are drawn connecting every two nodes (called arcs or edges). A distance (or cost) is associated with every edge. If in a graph edges are drawn connecting any two nodes, then the graph is said to be *complete*. A round-trip of the cities corresponds to a special subset of the lines when each city is visited exactly once, and it is called a tour or a Hamiltonian cycle in graph theory. The length of a tour is the sum of the lengths of the lines in the round-trip.

ISBN: 978-989-95079-6-8

Asymmetric and symmetric TSPs can be distinguished depending on if any edge of the graph is directed or not. To formulate the symmetric case with n nodes $c_{ij} = c_{ji}$, so a graph can be considered where there is only one arc (undirected) between every two nodes. Let $x_{ij} = \{0,1\}$ be the decision variable ($i= 1,2,\ldots,n$ and $j=1,2,\ldots,n$), and $x_{ij} = 1$, means that the arc connecting node$_i$ to node$_j$ is an element of the tour.

Let $x_{ii} = 0$ ($i= 1,2,\ldots,n$) (1)

meaning that no tour element is allowed from a node to itself. Furthermore

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} = n \qquad (2)$$

that is the number of decision variables where $x_{ij} = 1$ is equal to n, and

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad \forall j \in \{1,2,\ldots,n\}, \qquad (3)$$

$$\sum_{j=1}^{n} x_{ij} = 1 \qquad \forall i \in \{1,2,\ldots,n\}, \qquad (4)$$

meaning that each column and row of the decision matrix has a single element with a value 1 (i.e., each city is visited once). For assuring the close circuit, an additional constraint must be set. A permutation of nodes $(p_1,p_2,\ldots.p_n)$ has to be constructed so that the total cost $C(p)$ is minimal:

$$\text{minimize} \quad C(p) = \left(\sum_{i=1}^{n-1} c_{p_i, p_{i+1}}\right) + c_{p_n, p_1}. \qquad (5)$$

For a symmetrical network there are $1/2\ (n-1)!$ possible tours (because the degree of freedom is $(n-1)$ and tours describing the same sequence but opposite directions are not considered as different tours) and for asymmetric networks where $c_{ij} \neq c_{ji}$ the number of possible tours is $(n-1)!$. Some reduction can be done [14], a guarantee that is proportional to $n^2 2^n$ can be given, however it is clear that an exhaustive search is not possible for large n in practice. Rather than enumerating all possibilities, successful algorithms for solving the TSP problem have been capable of eliminating most of the roundtrips without ever actually considering them. The main groups of engines are [5-12]:

- Mixed-integer programming
- Branch-and-bound method
- Heuristic searches (local search algorithms, simulated annealing, neural networks, genetic algorithms, particle swarm optimization, ant colony optimization, etc.)

In this paper a eugenic bacterial memetic algorithm is proposed as a novel heuristic search for TSP.

3 Variable costs and consequences of their nature

3.1 *Costs in real road networks*

Considering real road transport networks, especially in city logistics, the actual circumstances and condition of the transit process are subject to not only the topography of the given network but to timing as well. Referring to the phenomenon of cyclic peak-hours and also to the weekly (monthly, yearly) periodicity of traffic on road, it can be stated that the unit cost of traveling is also a variable, and it can be described as a time series rather than a constant value. The main reasons of that are the following:

- The actual cost of 1 km depends on the current fuel consumption, which is partly affected by the speed, but the speed is externally determined by the current traffic.
- A relatively large proportion of transportation cost is the cost of labor (i.e., wages of drivers), which is calculated on driving time. In Europe distance-based payment for commercial drivers are not allowed according to the European Agreement Concerning the Work of Crews of Vehicles Engaged in International Road Transport (AETR).
- The return on equity capital is a vital issue for haulage companies, since the transportation sector of the economy is a capital intensive one, meaning that utilization of vehicle in time is a crucial problem.

In addition, during long-distance shipments the drivers occasionally must stop for a rest (according to AETR) at a minimum 11 hour period (often overnight), and very often week-end traffic restrictions for heavy vehicles are introduced.

Considering the uncertainty of relevant data it can be stated, that one's estimated travel time by automobile between two points is a case of possibility due to the measurement imprecision and perception. It can be seen that the circumstances and conditions are significantly changing in time that is the actual value of cost matrix element c_{ij} should be subject to timing of transit between node$_i$ and node$_j$ and an appropriate representation of imprecision can be the use of fuzzy numbers. In this sense geographical optimization alone is not appropriate, and the road transport operation has to be scheduled in time as well.

3.2 *The modified TSP, the Fuzzy Road Transport Traveling Salesman Problem (FRTTSP)*

For fulfilling the requirements of realistic road transport processes, we propose the following modification to the classical TSP [23].

Since the overall target is to achieve the cheapest tour (in monetary terms), the constraint that each node (city) is visited exactly once is skipped. Calculating with time-dependent cost coefficients that are not necessarily proportional to distances, a longer route can be a cheaper one, and as a consequence some nodes can be visited more than once. Thus in the FRTTSP we eliminate restrictions (2), (3) and (4).

If a significant improvement in traffic conditions can be expected, that is a future value of a cost c_{ij} will be less then its present value, it is worth waiting (suspending the tour for a while) and continuing in the next step. In this case obviously the cost of staying at a point must be calculated. In this sense we eliminate restriction (1) as well. Very often in the solutions restriction (1) is fulfilled by selecting $c_{ii} = \infty$. In our case c_{ii} is the cost of staying at node$_i$ in a given step.

ISBN: 978-989-95079-6-8

The permutation of nodes ($p_1, p_2, \ldots p_n$) is being modified as well. As a city may be visited several times, objective function (5) must be rewritten:

$$\text{minimize } C(p) = \left(\sum_{i=1}^{mn-1} c_{p_i, p_{i+1}} \right) + c_{p_{mn}, p_1}, \qquad (6)$$

where $m=1,2,\ldots$ is the multiplier factor. Objective function (6) is a generalized form of TSP, the multiplier factor equals to 1 in the classical cases.

In order to represent the uncertainty triangular fuzzy numbers are used as cost coefficients. Triangular fuzzy numbers have a membership function consisting of two linear segments joined at a peak, so they can be constructed easily on the basis of little information: the supporting interval $C=[c_1, c_2]$ as the smallest and the largest possible values, and c_M which is the peak value where the membership function equals to 1. In that case the triangular fuzzy number is denoted by $\boldsymbol{C} = (c_1, c_M, c_2)$.

When the distances between the cities are described by fuzzy numbers, it must be discussed how these fuzzy numbers are summed up in a tour in order to calculate the total distance. The arithmetic of fuzzy numbers is based on the extension principle [18]. We are using triangular shaped fuzzy numbers which can be characterized by three values, the boundaries of the support and the core value. When we calculate the total distance of a tour, then instead of adding fuzzy numbers by the extension principle, we can do an easier calculation based on the defuzzified values of the fuzzy numbers. According to [16], some defuzzification method has invariance properties meaning that the result is invariant under linear transformations, thus there is no need to determine the whole outcome using the extension principle but only to compute the sum of the defuzzified values of each fuzzy number. If we are using triangular shaped fuzzy numbers then the Averaging Level Cuts (ALC) type defuzzification method used in [16] gives the same result as the Center of Gravity (COG) method. So, in the first step the fuzzy numbers are defuzzified by the COG method (which is simply the arithmetic mean of the three characteristic points of the fuzzy number) and then these crisp numbers are summed up providing the total distance of the tour.

4 Eugenic bacterial memetic algorithms

Nature inspired some evolutionary optimization algorithms suitable for global optimization of even non-linear, high-dimensional, multi-modal, and discontinuous problems. The original genetic algorithm was developed by Holland [1] and was based on the process of evolution of biological organisms. It uses three operators: reproduction, crossover and mutation. Later, new kind of evolutionary based techniques were proposed, which are imitating phenomena that can be found in nature.

Bacterial Evolutionary Algorithm (BEA) [2] is one of these techniques. BEA uses two operators; the bacterial mutation and the gene transfer operation. These new operators are based on the microbial evolution phenomenon. Bacteria share chunks of their genes rather than perform a neat crossover in chromosomes. The bacterial mutation operation optimizes the chromosome of one bacterium; the gene transfer operation allows the transfer of information between the bacteria in the population. Each bacterium represents a solution for the original problem. BEA has been applied for wide range of problems, for instance optimizing the fuzzy rule bases [2, 3] or feature selection [4].

Evolutionary algorithms are global searchers, however in most of the cases they give only a quasi-optimal solution for the problem. Local search approaches can give more accurate solution, however they are searching for the solution only in a local area of the search space. Local search approaches might be useful in improving the performance of the basic evolutionary algorithm, which may find the global optimum with sufficient precision in this combined way. Combinations of evolutionary and local-search methods are usually referred to as memetic algorithms [19]. A new kind of memetic algorithm based on the bacterial approach is the bacterial memetic algorithm (BMA) [20].

The algorithm consists of four steps. First, an initial population has to be created. Then, bacterial mutation, a local search and gene transfer are applied, until a stopping criterion is fulfilled. The bacterial mutation is applied to each chromosome one by one. First, N_{clones} copies (clones) of the bacterium are generated, then a certain segment of the chromosome is randomly selected and the parameters of this selected segment are randomly changed in each clone (mutation). Next all the clones and the original bacterium are evaluated and the best individual is selected. This individual transfers the mutated segment into the other individuals. This process continues until all of the segments of the chromosome have been mutated and tested. At the end of this process the clones are eliminated. After the bacterial mutation operator a local search is applied for each individual. This method depends on the given problem. For the TSP it is detailed in the next section.

In the next step the other evolutionary operation, the gene transfer is applied, which allows the recombination of genetic information between two bacteria. First, the population must be divided into two halves. The better bacteria are called the superior half, the other bacteria are called the inferior half. One bacterium is randomly chosen from the superior half, this will be the source bacterium and another is randomly chosen from the inferior half, this will be the destination bacterium. A segment from the source bacterium is chosen randomly and this segment will overwrite a segment of the destination bacterium or it will be added to the destination bacterium. This process is repeated for N_{inf} times. The stopping condition is usually given by a predefined maximum generation number (N_{gen}). When N_{gen} is achieved then the algorithm ends otherwise it continues with the bacterial mutation step. We use eugenic elements also in the algorithm [21]. This reflects the human's decision will, and puts some deterministic element into the algorithm. Details will be given in the next section.

The basic algorithm has four parameters: the number of generations (N_{gen}), the number of bacteria in the population (N_{ind}), the number of clones in the bacterial mutation (N_{clones}), and the number of infections (N_{inf}) in the gene transfer operation.

ISBN: 978-989-95079-6-8

5 EBMA for the modified traveling salesman problem

When applying evolutionary type algorithms first of all the encoding method must be defined. The evaluation of the individuals has to be discussed, too. The operations of the algorithm have to be adapted to the given problem.

5.1 Encoding method and evaluation of the individuals

In the modified traveling salesman problem one city may be visited more than once. Because each city must be visited at least once, one solution of the problem does not need to be a permutation of the cities. The evident encoding of the problem into a bacterium is simply the enumeration of the cities in the order they should be visited. Therefore, a length of the bacterium may be greater than the number of cities (N_{cities}), but an upper bound for the bacterium length has to be defined too, we allow bacteria not longer than $m \cdot N_{cities}$, where m is the multiplier factor, which is a parameter of the algorithm (usually m=2). The initial city is not represented in the bacterium.

The length of the bacteria can be changeable. It can be changing during the evolutionary process and the individuals can have different lengths. In the initial population generation, the length of the bacteria is a random number greater than or equal to N_{cities} and less than or equal to $m \cdot N_{cities}$.

The evaluation of a bacterium is based on the time dependent distance matrix. The distance between the first element of the bacterium and the initial city is taken from the distance matrix at the zeroth time step, the distance between the second element of the bacterium and the first element of the bacterium is taken from the distance matrix at the first time step, and so on, these distances are summed up, and the total distance is obtained in this way.

5.2 Bacterial mutation

In the bacterial mutation there is an additional parameter, the length of the segment to be mutated in the clones. First, the segments of the bacterium are determined, and a random segment order is created. In the clones, the mutation of the given segment is executed. For example in Figure 1, the length of the segment is 3, and there are 4 clones. The random segment order is e.g., {3rd segment, 1st segment, 4th segment, 2nd segment}. This means that in the first sub-cycle of bacterial mutation, the 3rd segment is mutated in the clones. After the mutation of the clones, the best one is being chosen, and this clone (or the un-mutated original bacterium) transfers the mutated segment to the other individuals.

The segments of the bacterium do not need to consist of consecutive elements. The elements of the segments can come from different parts of the bacterium as it can be seen in Figure 2.

Because in the modified TSP the number of visited cities is not predefined, bacteria with different length can occur in the population. Although in the initial population generation bacteria with different length can arise we would like to allow the changes in the length within the bacterial operations, too. Therefore before a clone is mutated a random value is used for determining that after the mutation the length of the clone will increase, decrease or remain the same.

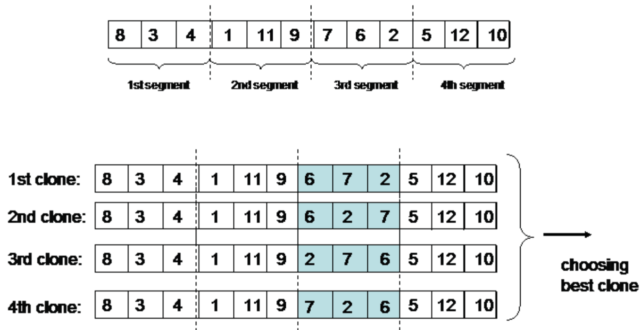

Figure 1: Bacterial mutation

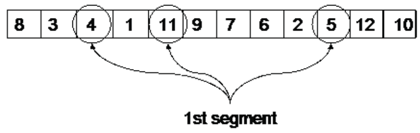

Figure 2: Segment in the bacterial mutation

Increasing is allowed only in the case, when the maximum bacterium length ($m \cdot N_{cities}$) is not exceeded, similarly, decreasing is allowed only in the case, when the minimum bacterium length (N_{cities}) is guaranteed. If the length will increase, then besides changing the positions of the cities in the selected segment of the clone, new cities are added to this clone randomly. If it will decrease, then some cities are deleted from the clone taking care that only those cities are allowed to be deleted, which have at least one other occurrence in the clone. If the length remains the same, then only the positions of the cities in the selected segment are changed.

5.3 Local search method

A tour can be improved by some local heuristics. One of the most successful methods is the Lin-Kernighan algorithm [22] which based on the k-opt algorithm. The k-opt algorithm removes k edges from the tour and reconnects the k paths optimally. We applied the 2-opt and 3-opt technique in our EBMA algorithm. For higher value of k the algorithm would take more time and would provide only small improvements on the 2-opt and 3-opt techniques.

5.4 Gene transfer

In the gene transfer operation there is also an additional parameter, the length of the segment to be transferred from the source bacterium to the destination bacterium. In contrast with the bacterial mutation, in the gene transfer, the segment can contain only consecutive elements within the bacterium. The reason for that is the segment containing consecutive elements representing sub-tours in the bacterium, and transferring good sub-tours is the main goal of the gene transfer operation.

Figure 3 shows the gene transfer in the case of time independent distance matrix. In the case of time dependent

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distance matrix, the position where the transferred segment goes to in the destination bacterium must be the same as the position of the segment in the source bacterium.

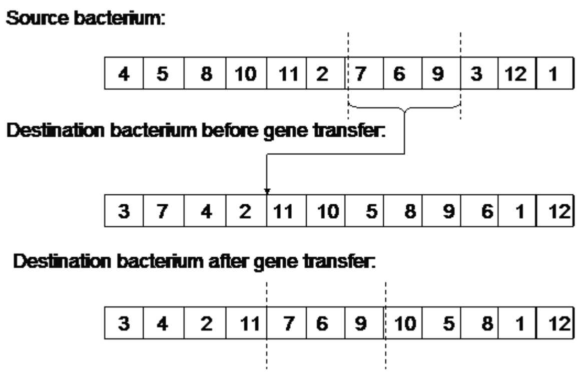

Figure 3: Gene transfer

The different individual lengths are allowed also in the gene transfer operation. After the segment was transferred to the destination bacterium, the elements that occur in the transferred segment and are already in the destination bacterium can be deleted from the destination bacterium. If the same number of elements is deleted from the destination bacterium as the length of the segment, then the length of the destination bacterium remains the same. If less elements are deleted, then its length will be increasing. If more elements are deleted (taking care that each city must have at least one occurrence in the bacterium), then the length will be decreasing. We must also take care that the length of the destination bacterium must be at least N_{cities} and at most $m{\cdot}N_{cities}$.

5.5 Eugenic elements

Eugenic is used in the initial population creation and in the bacterial mutation operator. This means that we put more determinism into the algorithm which contains normally the deterministic local search and the stochastic evolutionary operators. During the initial population creation not only random individuals are generated but also some deterministic ones according to the following rule: there is an individual, which represents the tour in which always the nearest unvisited city is visited. There can be another initial bacterium, which represents the tour in which alternating the nearest and the second nearest city is visited. There can be a third individual, where always the second nearest city is taken.
In the bacterial mutation not only randomly mutated clones are produced, but there will always be a deterministic clone, which performs a reverse ordering permutation on the selected segment. According to our experiences this can be effective in solving TSP like problems.

6 Computational results

First the efficiency of the proposed algorithm is presented. Fig. 4 and 5 compare the computational result against a “classical” reference instance TSP (www.tsp.gatech.edu, XQF131). The total length of the optimal tour is *564*, the solution of our proposed algorithm is *566*, the computational error is *0.35%*.

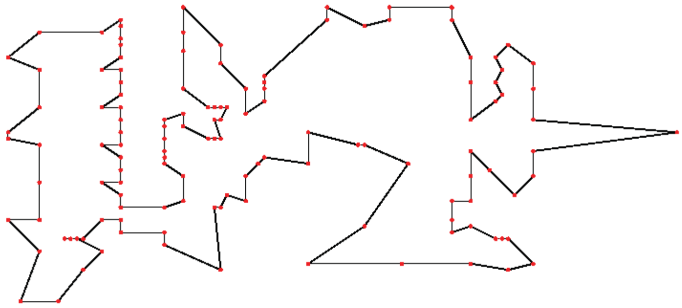

Figure 4: Reference instance (www.tsp.gatech.edu)

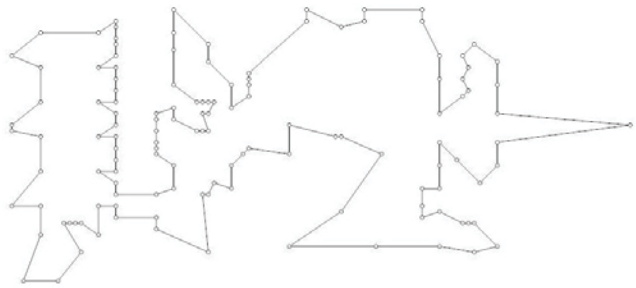

Figure 5: Solution of reference instance by the EBMA

Next in the evaluation process a classic symmetric graph is compared to an asymmetric and time dependent version of the same graph. Solution for the symmetric case is shown in Fig. 6.
The RTTSP version is modified in the following points:
$Node_{16}$ has only one connection to $node_6$.
$Node_6$ has two connections, to $node_{16}$ and to $node_9$.

$$C_{1,23}(t) = C_{1,23} + 0.05t$$
$$C_{20,0}(t) = C_{20,0} + 0.01t$$
$$C_{13,0}(t) = C_{13,0} + 0.02t$$

where *t* is the step in which the tour visits the node. This is a very simple representation of the time dependency of the graph. The results are shown in Fig. 7.
Since the running time of EBMA is about proportional to the number of generations it is a crucial task to select the most efficient parameters:

- number of bacteria in the population (N_{ind})
- number of clones in the bacterial mutation (N_{clones})
- number of infections (N_{inf}) in the gene transfer operation
- length of the segment to be mutated
- length of the segment to be transferred.

Finally the fuzzy cost coefficients are considered, results are shown in Fig. 8. Let the fuzzy values are:

$$\boldsymbol{C}_{2,0} = (0.015, 0.1986, 0.4)$$
$$\boldsymbol{C}_{0,2} = (0.001, 0.1986, 0.2)$$
$$\boldsymbol{C}_{23,4} = (0.1, 0.4504, 0.5)$$
$$\boldsymbol{C}_{4,23} = (0.4, 0.4504, 0.7)$$
$$\boldsymbol{C}_{26,29}(t) = (0.05, 0.1655, 0.2)\ 0.05\ t$$

ISBN: 978-989-95079-6-8

$$\mathbf{C}_{29,26}(t)= (0.11,\ 0.1655,\ 0.3)\ 0.05\ t$$
$$\mathbf{C}_{10,4}(t)= (0.03,\ 0.1449,\ 0.16)\ 0.06\ t$$
$$\mathbf{C}_{4,10}(t)= (0.12,\ 0.1449,\ 0.3)\ 0.06\ t$$
$$\mathbf{C}_{17,18}(t)= (0.15,\ 0.267,\ 0.3)+0.05\ t$$
$$\mathbf{C}_{18,17}(t)= (0.15,\ 0.267,\ 0.3)-0.01\ t$$
$$\mathbf{C}_{7,23}(t)= (0.1,\ 0.18,\ 0.25)+0.01\ t$$
$$\mathbf{C}_{23,7}(t)= (0.1,\ 0.18,\ 0.25)-0.01\ t$$
$$\mathbf{C}_{0,21}(t)= (0.01,\ 0.066,\ 0.10)+0.02\ t$$
$$\mathbf{C}_{21,0}(t)= (0.01,\ 0.066,\ 0.10)-0.02\ t$$

(Remark: peak values are kept from the crisp matrix.)

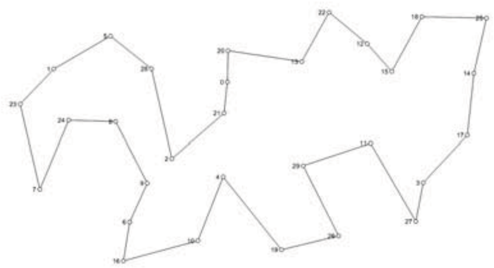

Figure 6: Graphical representation of the best tour of TSP

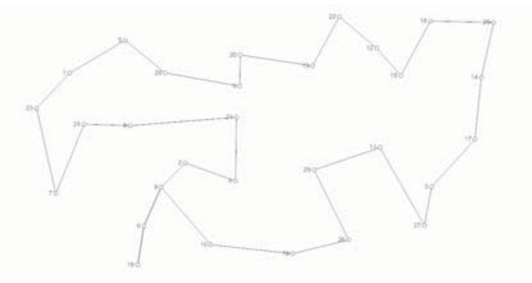

Figure 7: Graphical representation of the best tour in RTTSP

Figure 8: Graphical representation of the best tour in FRTTSP

The scope of future research activity is to set general rules that can give instructions in order to find the most efficient parameters of EBMA according to the size and other (e.g. topographical) features of a given FRTTSP, since running time is significantly affected by those parameters.

Acknowledgment

This paper was supported by the Széchenyi University Main Research Direction Grant 2009, and a National Scientific Research Fund Grant OTKA T048832 and K75711.

References

[1] Holland, J. H.: *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, The MIT Press, Cambridge (1992)

[2] Nawa, N. E., Furuhashi, T.: *Fuzzy System Parameters Discovery by Bacterial Evolutionary Algorithm*, IEEE Tr. Fuzzy Systems 7 (1999) pp. 608-616

[3] Botzheim, J., Hámori, B., Kóczy, L. T., Ruano, A. E.: *Bacterial algorithm applied for fuzzy rule extraction*, in Proceedings of the International Conference on Information Processing and Management of Uncertainty in Knowledge-based Systems, Annecy, France (2002) pp. 1021-1026

[4] Botzheim J., Drobics M., Kóczy L. T.: *Feature selection using bacterial optimization*, in Proceedings of the International Conference on Information Processing and Management of Uncertainty in Knowledge-based Systems, IPMU 2004, Perugia, Italy, (July 2004) pp. 797–804

[5] Applegate, D.L., Bixby, R.E., Chvátal, V., Cook, W.J.: *The Traveling Salesman Problem, A Computational Study*, Princeton University Press, Princeton and Oxford (2006) pp. 10-11

[6] Yu-Hsin Liu : *A hybrid scatter search for the probabilistic traveling salesman problem*, Computers & Operations Research 34 (2007) pp. 2949-2963

[7] Teoh, E.J.,Tan, K.C., Tang, H.J., Xiang, C., Goh, C.K.: *An asynchronous recurrent linear threshold network approach to solving the traveling salesman problem*, Neurocomputing 71 (2008) pp. 1359-1372

[8] Ding, C., Cheng, Y., He, M.: *Two-Level Genetic algorithm for Clustered Traveling Salesman Problem with Application in Large-Scale TSPs*, Tsinghua Science and Technology, Vol.12.No.4 (2007) pp. 459-465

[9] Hsiao-Fan Wang, Yu-Pin Wen: *Time-Constrained Chinese Postman Problems*, Computers and Mathematics with Applications 44 (2002) pp. 375-387

[10] Shi, X.C., Liang, Y.C., Lee, H.P., Lu, C., Wang, Q.X.: *Particle swarm optimization-based algorithms for TSP and generalized TSP*, Information Processing Letters 103 (2007) pp. 169-176

[11] Bontoux, B., Feillet, D.: *Ant colony optimization for the traveling purchaser problem,* Computers & Operations Research 35 (2008) pp. 628-637

[12] Yu-Wan Chen, Yong-Zai Lu, Penf Chen: *Optimization with extremal dynamics for the traveling salesman problem*, Physica A 385 (2007) pp. 115-123

[13] Guan-Chun Luh, Shih-Wei Lee: *A bacterial evolutionary algorithm for the job shop scheduling problem,* Journal of the Chinese Institute of Industrial Engineers, Vol. 23, No. 3, (2006) pp. 185-191

[14] Held, M.R., Karp R.M.: *A dynamic programming approaches to sequencing problems*, Journal of the Society of Industrial and Applied Mathematics 10 (1962) pp. 196-210

[15] Ammar,E.E., Youness, E.A.: *Study on multiobjective transportation problem with fuzzy numbers*, Applied Mathematics and Computation 166 (2005) pp. 241-253

[16] Oussalah, M.: *On the compability between defuzzification and fuzzy arithmetic operations*, Fuzzy Sets and Systems 128 (2002) pp. 247-260

[17] Kikuchi, S., Chakroborty, P.: *Place of possibility theory in transportation analysis*, Transportation Research Part B 40 (2006) pp 595-615

[18] Zadeh, L.A.: *The concept of linguistic variable and its application to approximate reasoning*, Inform. Sci. Part 1, 8 (1975) 199-249, Part 2, 301-357, Part 3, 9 (1975) 43-80.

[19] Moscato P. *On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms*. Caltech Concurrent Computation Program, Tech. Rep., California, 1989.

[20] Botzheim J., Cabrita C., Kóczy L. T., and Ruano A. E., “*Fuzzy rule extraction by bacterial memetic algorithm*,” IFSA 2005, Beijing, China, 2005, pp.1563-1568.

[21] Ye J., Tanaka M., Tanino T.: *Eugenics-based genetic algorithm, IEICE Transactions on Information and Systems*, Vol. E79-D No. 5 pp. 600-607.

[22] Lin S., Kernighan B. W.: *An Effective Heuristic Algorithm for the Traveling-Salesman Problem*, Operations Research, 21, pp. 498-516 (1973).

[23] Földesi P., Botzheim J.: *Solution for modified traveling salesman problem with variable cost matrix using bacterial evolutionary algorithm*. Acta Technica Jaurinensis Series Logistica, 1(2):159–171, 2008.

ISBN: 978-989-95079-6-8