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City Assignment by Multi-Objective Evolutionary Artificial Neural Networks for Multiple TSP

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***Abstract*—In the multiple traveling salesman problem (TSP), a group of cities to be visited has been assigned to each salesman based only on the cities' geographic information, and the visiting routes of the salesmen are planned. However, there is no guarantee that the adopted clustering method is appropriate for route planning. In this study, we proposed a two-stage search method, where the clustering is performed using an artificial neural network, its weights are designed through a multi-objective evolutionary algorithm (MOEA), and each salesman's visiting route is solved using a TSP solver. We conducted computational experiments for a test problem to compare the performance of the proposed method to a canonical clustering method. Additionally, we examined the characteristics of the balanced solution selected from the obtained non-dominated solution set.**

***Index Terms*—multiple traveling salesman problem, multi-objective evolutionary algorithm, artificial neural networks, clustering**

I. Introduction

The TSP is a problem in which geographic information of multiple cities is given, and a salesman needs to find a route that visits all cities exactly once without duplicates and returns to the starting city [1] [2]. While the classic TSP deals with the route problem for a single salesman, the problem of determining the route for multiple salesmen assigned to visit specific cities is called the multiple traveling salesman problem (MTSP).

In MTSP, it has been common to perform assignments based only on cities' geographic information. Then, solving the TSP separately for each assigned city group is often used [3]. However, such an assignment is not guaranteed to reduce the total tour length or improve evaluation criteria specifically designed for applications categorized as TSP.

To address this issue, we propose a two-stage search method [3] using an artificial neural network (ANN) designed through multi-objective evolutionary computation to determine the assignment of the visiting city groups based on multiple evaluation criteria. We then solve the tour of the assigned city groups using an approximation algorithm widely adopted for TSP.

In this study, we conducted computational experiments using a test problem related to TSP to validate the effectiveness of the proposed method compared to a canonical clustering method. Additionally, we examined the characteristics of the balanced solution selected from the obtained non-dominated solution set.

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II. Objective Functions for MTSP

Let L_k represent the tour length of the k-th salesman ($k \in 1, 2, \cdots, K$), and K denotes the total number of available salesmen. In MTSP, we evaluate the tour lengths for all salesmen. This study calculates the average tour length by dividing the sum of tour lengths by the number of assigned salesmen, K', as shown in (2). This function motivates solutions to involve as many available salesmen as possible. Furthermore, we aim to equalize the tour lengths among all salesmen. For this purpose, we adopt a standard deviation of L_k, denoted by (3). Thus, we aim to solve a 2-objective minimization problem.

$$\text{minimize} \qquad F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x})) \tag{1}$$

$$f_1 = \frac{1}{K'} \sum_{k=1}^{K} L_k \tag{2}$$

$$f_2 = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (L_k - \frac{1}{K} \sum_{k=1}^{K} L_k)^2} \tag{3}$$

III. Evolutionary Multi-Objective Optimization

This study used a fully connected feedforward ANN to assign visiting cities. The input consists of normalized city coordinates, and the output represents the salesman k to be assigned. Each neuron's activation function was sigmoid. This setting allows us to partition the city coordinate plane nonlinearly. Furthermore, using MOEA to design the ANN, we can expect an adaptive assignment of visiting cities based on multiple evaluation criteria.

We applied the real-valued evolutionary algorithm MOEA/D-DE [4] to design the weights of the ANN. As the aggregation function for combining multiple single-objective optimization problems, this study used the Tchebycheff function. Here, we normalize f_1 in (2) and f_2 in (3).

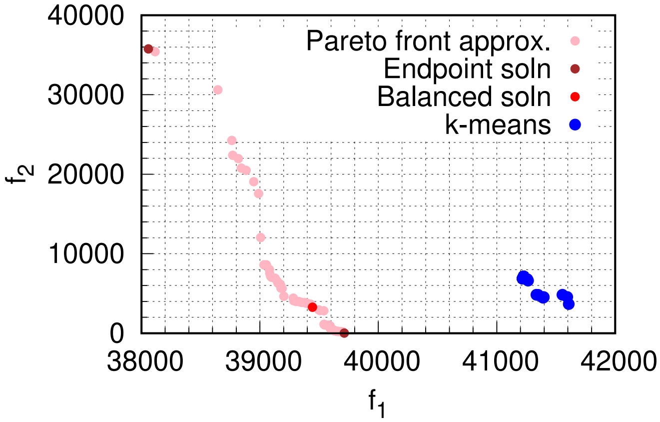
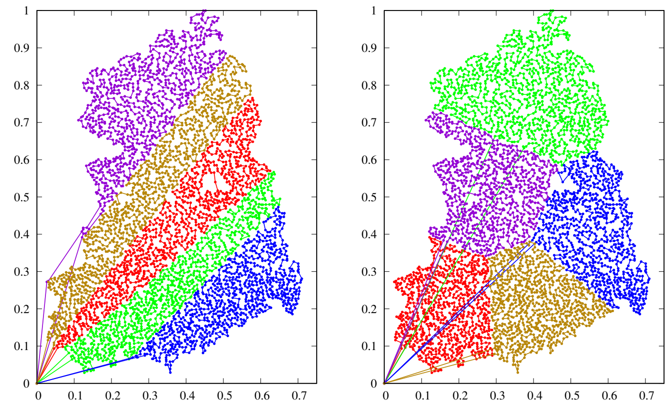


Fig. 1. Objective values for the proposed method and the k-means


(a) balanced solution (inv2)

(b) k-means

Fig. 2. Tours obtained for the proposed method and the k-means

TABLE I
THE TOUR LENGTHS AND OBJECTIVE VALUES

	inv1	inv2	inv3	k-means
L_1	47016.8	40350.7	39687.4	34392.3
L_2	1259.0	34471.5	39720.5	54045.1
L_3	43138.8	37345.9	39719.2	40895.8
L_4	97797.1	44100.0	39699.3	40579.7
L_5	1080.5	40946.8	39753.8	36176.9
f_1	38058.4	39443.0	39716.1	41218.0
f_2	35766.9	3282.9	22.6	6885.5

IV. Computer Simulations

A. Simulation Conditions

This study focused on the fnl4461 from the TSP benchmark. Furthermore, we set the departure city outside the convex hull formed by all city configurations except for the departure city. All salesmen share this city as their common departure city. Thus, the number of cities becomes 4462.

In this problem setting, the number of output nodes N_o of the ANN equals the number of possible salesmen K. In this study, we set the number of input nodes at 2, the number of hidden nodes at 4, and $K = 5$. We used the TSP approximation method LKH-2.0.9 [5] [6] to solve the TSP. We conducted ten trials of the proposed method. We saved all non-dominated solutions obtained during one run as an archive. We also conducted experiments with k-means for city assignment, using the same settings for LKH to compare the solutions obtained by the proposed method.

B. Simulation Results

We show the Pareto front approximation for a typical run of the proposed method and the objective values by the k-means in Fig. 1. The objective values of the solutions obtained by the proposed method have sufficiently converged over those by the k-means. We also present the balanced and endpoint solutions on the approximation as the most representative solutions for the obtained non-dominated solution set.

The tour lengths and objective values obtained are shown in Table I, where inv1 and inv3 indicate the endpoints and inv2 indicates the balanced solution. Firstly, inv1 represents a solution with a minimal value of f_1 and a large value of f_2. These values imply that inv1 assigns only a few cities to one or two salesmen, satisfying $K' = K$ while assigning most cities to the remaining salesmen. On the other hand, inv2 represents the balanced solution with the tour lengths uniformed and the small f_1 value. Finally, inv3 has considerable tour lengths and slight deviations among the tour lengths. The objective values of inv2 and inv3 are smaller than those of the k-means.

We show the tours for inv2 and k-means in Fig. 2. In these figures, each color represents the tour of one salesman. The appearance of stripe-like clusters is a characteristic feature of the proposed method observed when the departure city is placed outside all the cities, compared to the k-means.

V. Conclusion

In this study, we proposed a method for MTSP using the MOEA and ANN design for city assignment. We conducted computational experiments using a test problem to verify the effectiveness of the proposed method. Additionally, we examined the characteristics of the representative solutions. Consequently, the proposed method's balanced solutions form short tours equalized among each salesman. In the future, we plan to address problems with constraints on the tour lengths of each salesman. Additionally, we aim to apply the proposed method to real-world problems.

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