Tour Routes Planning with Matrix-based Differential Evolution

Pei-Fa Sun, Jian-Yu Li, Ming-Yu Li, Zhan-Yang Gao, Hu Jin, Sang-Woon Jeon, and Jun Zhang
Department of Electrical and Electronic Engineering
Hanyang University
Ansan 15588, South Korea

***Abstract*—Tourism is an important industry sector that requires tour companies to plan multiple routes for different tour groups, which is called tour multi-route planning. This paper focuses on tour multi-route planning, which can improve the economic benefit and allocation efficiency of tour resources. In this paper, we propose a novel multiple routes planning model that captures the real-world tourism scenario and practical constraints. We use matrix-based differential evolution to optimize the proposed model. Numerical evaluation results show the matrix-based differential evolution can be effective to optimize the proposed model.**

I. Introduction

According to the 2020 policy brief by the United Nations, tourism is a vital industry for many countries and regions, contributing more than 20 percent of their gross domestic product (GDP) and ranking as the world's third-largest export sector [1]. Tourism and tour agencies face the intricate challenge of designing numerous routes concurrently for their groups, which can number anywhere from a handful to several dozens. Strategically planning these multi-routes can lead to significant cost reductions and potentially attract a broader customer base for these agencies. However, multi-route design is not merely about identifying the briefest pathways. It is a complex procedure with numerous considerations and limitations. Traditional algorithms, such as Dijkstra's, often fall short in adequately addressing these multi-route challenges. [2], [3]. Furthermore, a strategy to efficiently optimize such complicated systems is required, not least as the number of tour groups and the corresponding constraints increase.

It is worthwhile to mention that evolutionary computation (EC) can plan tour routes using only the publicly available data, which is very useful for helping tour companies plan multiple tour routes. The work in [4] used the genetic algorithm (GA) and simulated annealing to optimize the tour routes in Medulin, Croatia. In [5], [6], ant colony optimization (ACO) algorithms were applied for tour route planning and the work in [7] used particle swarm optimization (PSO) to optimize the tour route.

In previous discussions, we highlighted that tour multi-route planning (TMRP) is essentially a multi-dimensional optimization process with numerous constraints. Addressing these intricate issues, inspired by matrix-based EC proposed in [8], we propose a matrix-based differential evolution (matrix-based DE). This approach offers two primary strengths: First, in contrast to the foundational algorithm, the matrix-based DE focuses entirely on matrix operations. These can be swiftly executed using high-level APIs in the dedicated scientific computing library. This compatibility facilitates leveraging the power of GPUs to expedite computations, which is crucial for ensuring adaptability in high-dimensional computing scenarios down the line. Secondly, it enables the incorporation of diverse linear algebra and matrix theory functions, allowing for intricate operations at the collective level. These processes significantly enhance our understanding of the population, endowing Evolutionary Computation (EC) with amplified potential. Our empirical assessments demonstrate the efficacy of the proposed matrix-centered DE in addressing TMRP challenges effectively.

II. Problem Model

A. TMRP Formulation

In this segment, we introduce the specifics of the TMRP model. The model incorporates M tourist attractions and P tour assemblies. For clarity in notation, we use the indices m and p to refer to the specific tourist attraction and the specific tour group, respectively, with m ranging from 1 to M and p from 1 to P. Each group, denoted by p, intends to explore n_p attractions out of the total M options, with n_p ranging from 1 to M. The travel itinerary for the pth group, represented as $\mathbf{r}_p$, encompasses these n_p chosen scenic spots. Specifically,

$$\mathbf{r}_p = \left[r_{p,1}, r_{p,2}, \ldots, r_{p,n_p}\right] \tag{1}$$

denotes an ordered set consisting of n_p scenic spots to visit in order by the pth tour group. That is, $\mathbf{r}_p$ is a subset of $[1 : M]^{n_p}$, ensuring that if $k \neq l$, then $r_{p,k}$ is distinct from $r_{p,l}$. We assume that each tour group embarks from the main tour center and concludes their journey at this starting point. Hence, the journey of the pth tour group begins at the tour center, ventures through scenic spots $r_{p,1}$ and $r_{p,2}$, and returns to the tour center after their visit to r_{p,n_p}.

In this study, we consider two specific costs for each tour group, represented by $C_{p,1}$ and $C_{p,2}$ for the pth group. The cost $C_{p,1}$ accounts for the transportation expenses associated with the geographical positions of the selected spots in $\mathbf{r}_p$. To provide clarity on this, $\mathbf{q}_0$ is the geographical coordinate of the tourist center, and $\mathbf{q}_m$ indicates the location of the mth

979-8-3503-1327-7/23/$31.00 ©2023 IEEE

site. Then the total tour distance of the pth tour group is given by

$$D_p = \left(\sum_{k=1}^{n_p - 1} d(\mathbf{q}_{r_{p,k}}, \mathbf{q}_{r_{p,k+1}}) \right) + d(\mathbf{q}_0, \mathbf{q}_{r_{p,1}}) + d(\mathbf{q}_{r_{p,n_p}}, \mathbf{q}_0), \tag{2}$$

where $d(\cdot)$ signifies the geometric distance between two distinct locations. Define $s_p > 0$ as the size of the pth tour group, representing the count of tourists, and $c_{\text{dis}} > 0$ as the transportation cost for each unit of distance. Consequently, $C_{p,1}$ can be articulated as

$$C_{p,1} = c_{\text{dis}} s_p D_p. \tag{3}$$

The subsequent cost, $C_{p,2}$, encompasses tour-related expenses, including ticket costs, food charges, lodging fees, among others, all groups on the choice of scenic spots in $\mathbf{r}_p$. Let $C_{p,m} > 0$ represent the cumulative tour cost when the pth tour group visit to the mth scenic spot. Subsequently, we deduce:

$$C_{p,2} = s_p \sum_{k=1}^{n_p} C_{p,r_{p,k}}. \tag{4}$$

In conjunction with the financial costs $C_{p,1}$ and $C_{p,2}$, we propose an additional cost $C_{p,3}$, which reflects the appeal or popularity of the chosen scenic spots in $\mathbf{r}_p$. The essence of $C_{p,3}$ is to prioritize more frequented scenic spots in $\mathbf{r}_p$ given a comparable financial expense, as this could lure a greater number of patrons to pay for the tour services. To this end, consider $R_m \in [1 : R_{\max}]$, which designates the standing of the mth scenic spot, a discrete value spanning from 1 to $R_{\max}$, gauging the scenic spot's fame. Notably, a rank of 1 indicates the premier scenic spot, with popularity decreasing as the rank ascends.

It is notable that $C_{p,3}$ ought to diminish when more scenic spots with lower rank values are incorporated in $\mathbf{r}_p$. A feasible method for representing this function is the exponential mapping e^{R_m}, granting heightened distinction based on the rank. As a result, $C_{p,3}$ can be represented as

$$C_{p,3} = \sum_{k=1}^{n_p} e^{R_{r_{p,k}}}. \tag{5}$$

Therefore, when the set of P tour routes $\{\mathbf{r}_p\}_{p=1}^{P}$ are given, the overall weighted sum cost is represented by

$$\sum_{p=1}^{P} (\alpha C_{p,1} + \beta C_{p,2} + \gamma C_{p,3}). \tag{6}$$

In this context, both $\alpha \in (0, 1]$ and $\beta \in (0, 1]$ serve as equilibrium coefficients between the two distinct financial costs. To be precise, a larger value of α compared to β signifies a preference for economically priced scenic spot, regardless of their proximity. Conversely, a higher β inclines towards choosing nearby scenic spots. The coefficient $\gamma > 0$ influences $\{\mathbf{r}_p\}_{p=1}^{P}$ to favor more sought-after scenic spots, provided it does not surpass the stipulated maximum financial threshold.

B. Constraints in TMRP

1) C1: Valid tour routes: The first constraint C1 is needed for valid tour routes. Obviously, $\text{card}(\mathbf{r}_p) = n_p$ should be satisfied and $r_{p,k} \neq r_{p,l}$ for all $k, l \in [1 : n_p]$ with $k \neq l$.

2) C2: Tour time constraints: The second constraint C2 is about the time constraint for each tour group. The total time consumption consists of two parts: the duration of time for sightseeing and the duration of time for transportation.

3) C3: Accommodation requirements: Note that some scenic spots have no accommodation of certain degrees or levels, such as the 5-star hotel. Therefore, tour companies should compensate consumers if the accommodation level does not reach the tour group's requirements.

4) C4: Load balancing between scenic spots: C4 is that certain authorities can limit the number of groups allocated by each tour company to a certain scenic spot over a period of time. We need to consider that the number of tour groups per scenic spot is less than the permit.

III. Matrix-based DE

The first step of matrix-based DE is to initialize the population. The formulation of this process is

$$\mathbf{X}^1 = [\mathbf{Ones}_{N\times 1} \times (\mathbf{U} - \mathbf{L})] \circ \mathbf{R}_{N\times D} + \mathbf{Ones}_{N\times 1} \times \mathbf{L}, \tag{7}$$

where $\mathbf{Ones}_{N\times 1}$ is a matrix with the shape of $N \times 1$, $\mathbf{R}_{N\times D}$ is a matrix with shape of $N \times D$ and filled up with the random number ranging from 0 to 1, and $\mathbf{U}$ and $\mathbf{L}$ are the upper bound and the lower bound.

Then, the mutation's formulation is

$$\mathbf{V}^g = \mathbf{X}^g_{[\mathbf{R}_1^*,\cdot]} + \mathbf{F} \circ \left(\mathbf{X}^g_{[\mathbf{R}_2^*,\cdot]} - \mathbf{X}^g_{[\mathbf{R}_3^*,\cdot]}\right), \tag{8}$$

in which $\mathbf{X}^g_{[\mathbf{R}_1^*,\cdot]}$, $\mathbf{X}^g_{[\mathbf{R}_2^*,\cdot]}$, and $\mathbf{X}^g_{[\mathbf{R}_3^*,\cdot]}$ are the three population matrices, individual of which are randomly chosen from the original population matrix.

The crossover is to select individuals from $\mathbf{V}^g$ and $\mathbf{X}^g$, that is

$$\mathbf{U}^g = \mathbf{V}^g \circ \mathbf{B}_C + \mathbf{X}^g \circ \overline{\mathbf{B}}_C, \tag{9}$$

where $\mathbf{B}_C$ is a Boolean matrix that indicates which individual will be selected and $\overline{\mathbf{B}}_C$ is the inverse matrix.

Define $f : \mathbb{R}^{N\times D} \to \mathbb{R}^{N\times 1}$ as the evaluation function. $f(\mathbf{X})$ will output a vector $\mathbf{E}$ including the fitness of all individuals. Compute the fitness of $\mathbf{U}^g$ and $\mathbf{X}^g$,

$$\mathbf{E}_{U^g} = f(\mathbf{U}^g),\ \mathbf{E}_{X^g} = f(\mathbf{X}^g), \tag{10}$$

respectively. Then, compare $\mathbf{E}_{U^g}$ and $\mathbf{E}_{X^g}$ as

$$\mathbf{B}_E = \mathbf{E}_{U^g} < \mathbf{E}_{X^g}. \tag{11}$$

Consequently, the new generation is

$$\mathbf{X}^{g+1} = \mathbf{U}^g \circ (\mathbf{B}_E \times \mathbf{Ones}_{1\times D}) + \mathbf{X}^g \circ (\overline{\mathbf{B}}_E \times \mathbf{Ones}_{1\times D}). \tag{12}$$

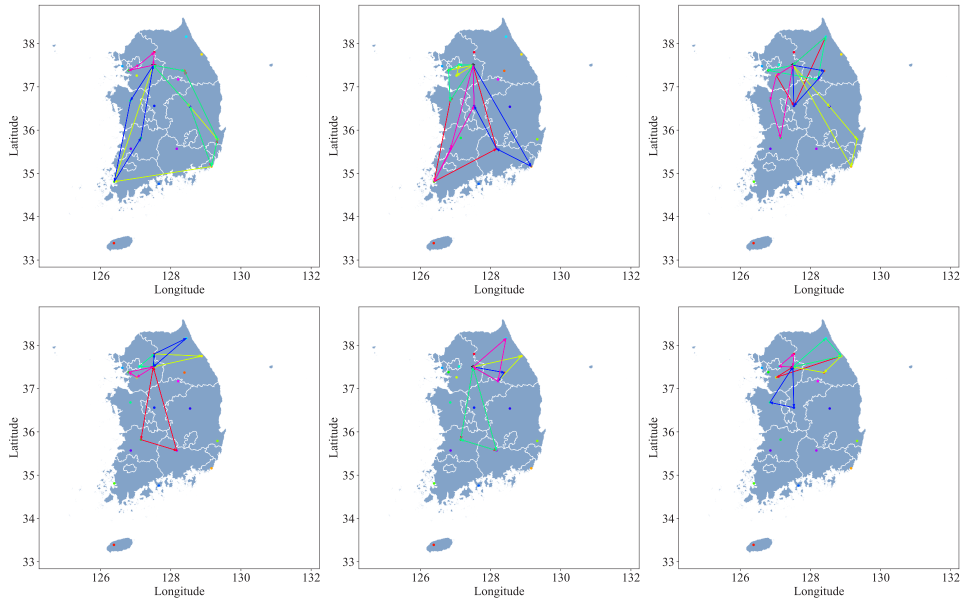

Fig. 1. 30 routes planning simultaneously optimized by Matrix-based DE with the population size 70. Each subgraph has 5 routes.

TABLE I
DATA OF TOUR GROUPS

Group Type	I	II	III	IV
Group Size	15	20	25	30
Scenic Spot	4	3	3	2
Tour Time	7	6	6	4
Hotel Rank	5	4	3	3
Quantity	3	5	7	15

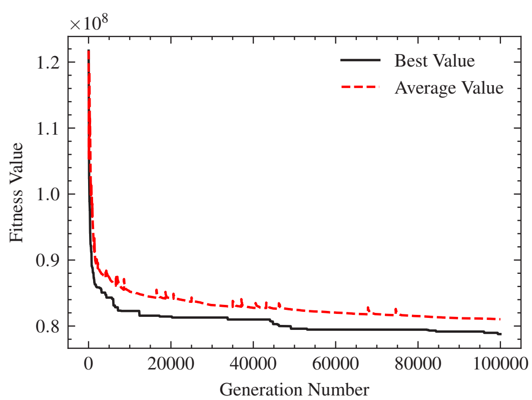

Fig. 2. Caption

IV. Numerical Evaluation

We collect 20 city data in Korea for simulation and use matrix-based EC to optimize the TMRP model. Moreover, we consult tour companies to get information of tour group types. Tab I shows the details of the tour group information. Figure 1 illustrates the result of the optimized route of 30 tour groups. Figure 2 shows the optimization process of matrix-based DE.

V. Conclusion

In this paper, we proposed a model regarding tour multiple-route planning. The model considers numerous real-world constraints. To optimize this model, we propose a matrix-based differential evolution method (inspired by matrix-based EC). The numerical evaluation results illustrate that matrix-based DE can optimize the proposed model effectively.

Acknowledgment

This work was supported in part by the National Research Foundation of Korea (NRF) funded by the Korean Government under Grants NRF-2020R1C1C1013806. Sang-Woon Jeon (sangwoonjeon@hanyang.ac.kr) is the corresponding author.

References

[1] U. Nations, "Policy brief: COVID-19 and transforming tourism," 2020.
[2] D. Fan and P. Shi, "Improvement of Dijkstra's algorithm and its application in route planning," in *IEEE International Conference on Fuzzy Systems and Knowledge Discovery*, vol. 4, 2010, pp. 1901–1904.
[3] A. Bozyiğit, G. Alankuş, and E. Nasiboğlu, "Public transport route planning: Modified Dijkstra's algorithm," in *IEEE International Conference on Computer Science and Engineering (UBMK)*, 2017, pp. 502–505.
[4] S. Baressi Šegota, I. Lorencin, K. Ohkura, and Z. Car, "On the traveling salesman problem in nautical environments: an evolutionary computing approach to optimization of tourist route paths in Medulin, Croatia," *Pomorski zbornik*, vol. 57, no. 1, pp. 71–87, 2019.
[5] S. Liang, T. Jiao, W. Du, and S. Qu, "An improved ant colony optimization algorithm based on context for tourism route planning," *PLoS One*, vol. 16, no. 9, 2021.
[6] S. Li, T. Luo, L. Wang, L. Xing, and T. Ren, "Tourism route optimization based on improved knowledge ant colony algorithm," *Complex & Intelligent Systems*, vol. 8, no. 5, pp. 3973–3988, 2022.
[7] B. Lu and C. Zhou, "Particle swarm algorithm and its application in tourism route design and optimization," *Computational Intelligence and Neuroscience*, vol. 2022, 2022.
[8] Z.-H. Zhan, J. Zhang, Y. Lin, J.-Y. Li, T. Huang, X.-Q. Guo, F.-F. Wei, S. Kwong, X.-Y. Zhang, and R. You, "Matrix-based evolutionary computation," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 6, no. 2, pp. 315–328, 2021.