Multi-objective Tourist Trip Design Problem in Chiang Mai City

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Abstract. This study aims to solve a multi-objective tourist trip design problem (MO-TTDP) in order to simultaneously maximize tourist satisfaction and minimize total traveling cost. The goal is to identify optimal routing for tourist under time window and time horizon constraints. The mathematical model is first presented to find optimal routing under limited budget. However, the exact algorithm cannot find solution with multiple objectives simultaneously. Therefore, this study applies a metaheuristic, called Global Local and Near-Neighbour Particle Swarm Optimization (GLNPSO), to solve the MO-TTDP. Several local search strategies are also proposed to enhance the solution quality. The proposed algorithm is implemented on the real-case study in Chiang Mai City, Thailand. The experimental results show that the proposed algorithm yields a set of diverse and high quality non-dominated solutions.

1. Introduction

Tourist trip design problem (TTDP) is defined as a route-planning problem for tourists in order to create a trip composed of a set or sequence of points-of-interests (POIs). The main objective of TTDP is to select POIs (or tourist attractions) that best satisfy tourist preferences under a set of constraints (e.g., travelling budget, visiting time at each POI, time window of POIs, time horizon/day). Typically, the types of TTDP are classified based on the number of derived routings or the number of travelling days; 1) a single tour variants of TTDP and 2) multiple tour variants of TTDP. The single tour variants of TTDP aim at finding an optimal routing for one day trip and can be modelled as Orienteering Problems (OP). The multiple tour variants of TTDP determine multiple routings based on the number of tourist’s visiting days and can be modelled as Team Orienteering Problems (TOP).

Damianos et.al [1] provided an intensive survey on solution approaches for solving TTDP with various sets of constraints. According to [1], TTDP is NP-hard in which exact algorithms can only find optimal solution for small-size problem with a small number of nodes. Thus, approximate algorithms such as heuristic and metaheuristic approaches are more preferable to deal with TTDP complexity especially when large number of nodes is considered. Tang and Miller-Hooks (2005) [2] proposed a Tabu Search (TS) heuristic with an adaptive memory procedure to improve the efficiency of the search for solving TTDP with a single tour. Archetti et al. [3] presented three metaheuristic solution techniques (TS and two variable neighborhood search, VNS) to solve TTDP. Ke et al. [4] proposed an Ant Colony Optimization-based algorithm (ACO) for TTDP. The results showed that the proposed ACO provided as good as the results obtained by [3] with faster computing time. Schilde et al. [5] introduced two metaheuristic approaches (ACO and an extension of VNS) for solving multi-objective TTDP. Later,
Bouly et al. [6] proposed another effective metaheuristic technique called a memetic algorithm (MA) with several local search techniques to solve the TTDP. Muthuswamy et al. [7] differently tackled the TTDP by applying Discrete Particle Swarm Optimization (DPSO) to generate one day trip at a time. Some local search techniques were added to enhance the quality of solutions. The DPSO showed its superior performances to other seven heuristic algorithms. In [8], particle swarm optimization inspired algorithm (PSOiA) was proposed by Dang et al in 2013 to deal with TTDP. The results showed that the proposed PSOiA outperforms all previously proposed heuristics. Labadi et al. [9] developed a local search heuristic technique for the TTDP with time window based on variable neighborhood structure. Yu et al. [10] introduced a new variant of orienteering problem with time window in which several types of transportation within a single tour are taken into consideration. The result showed that PSO provides good solution quality with fast computing time. This study presented an application of an effective metaheuristic, called Global Local and Near-Neighbour Particle Swarm Optimization (GLNPSO), to solve multi-objective TTDP (MO-TTDP). The objective is to design tourist optimal routes that simultaneously maximize tourist satisfaction and minimize total traveling cost. Several local search strategies are also proposed to enhance the solution quality. The remainder of this paper is organized as follows. Section 2 presents a mathematical model of the TTDP. Section 2 provides an application of GLNPSO algorithm to deal with the problem. The proposed algorithm is implemented on the real-case study in Chiang Mai City, which is one of the most popular tourist attractive cities in Thailand. Thus, the experimental results are reported in Section 4. Finally, the conclusion is given in Section 5.

2. Mathematical Model
The problem is mathematically formulated as a mixed-integer programming (MIP) as follows.

Index
\(i, j\): Tourist attraction (\(i, j = 2, 3, \ldots, N\)) and accommodation (\(i, j = 1\))
\(k\): Travelling day (\(k = 1, 2, \ldots, M\))

Decision variables
\(X_{ijk}\): 1 if a tourist travel from attraction \(i\) to attraction \(j\) on day \(k\) or 0 otherwise
\(Y_{ik}\): 1 if a tourist visits attraction \(i\) on day \(k\) or 0 otherwise
\(A_{ik}\): Arrival time at attraction \(i\) on day \(k\)
\(PD_{ik}\): Departure time from attraction \(i\) on day \(k\)
\(E_{k}\): End time of tourist routing on day \(k\)

Parameter
\(N\): Number of tourist attractions and accommodations; \(n = \{1, 2, \ldots, N\}\)
\(M\): Number of travelling days; \(k = \{1, 2, \ldots, M\}\)
\(U_{i}, U_{j}\): Constant value used to eliminate sub-tours
\(C_{ij}\): Travelling cost from attraction \(i\) to attraction \(j\) on day \(k\)
\(RC_{i}\): Travelling Cost at attraction \(i\)
\(S_{i}\): Satisfaction score of attraction \(i\)
\(t_{ij}\): Travelling time from attraction \(i\) to attraction \(j\)
\(R_{i}\): Estimated time spent at attraction \(i\)
\(TW_{\text{min}}\): Minimum time window of attraction \(i\)
\(TW_{\text{max}}\): Maximum time window of attraction \(i\)
\(L\): A large number
\(T_{\text{max}}\): Maximum time horizon
\(T\): Ready time
\(B\): Budget

Objective function:
Max = \sum_{i}^{N} \sum_{k}^{M} S_i Y_{ik} \tag{1}

Constraints:

\[ \sum_{i=1}^{N} \sum_{k=1}^{K} X_{ijk} \leq 1, \forall i; i = \{2, \ldots, n\} \tag{2} \]

\[ \sum_{i=1}^{N} \sum_{k=1}^{K} X_{ijk} \leq 1, \forall j; j = \{2, \ldots, n\} \tag{3} \]

\[ X_{ijk} = Y_{jk}, \forall j; j = \{2, \ldots, n\} \tag{4} \]

\[ X_{ijk} = Y_{ik}, \forall i; i = \{1,2, \ldots, n\} \tag{5} \]

\[ \sum_{i=1}^{N} X_{ijk} \leq 1, \forall k; k = \{1,2, \ldots, m\} \tag{6} \]

\[ \sum_{i=2}^{N} X_{ijk} \leq 1, \forall i; i = \{1,2, \ldots, \} \tag{7} \]

\[ \sum_{i=1}^{N} \sum_{k=1}^{K} \left( C_{ij} + CR_{ij} \right) \cdot X_{ijk} \leq B \tag{8} \]

\[ \sum_{i=1}^{N} \sum_{k=1}^{K} \left( A_{ik} + R_i + t_{ij} \right) - L \times \left( 1 - X_{ijk} \right) \leq A_{jk}, \forall k; k = \{1,2, \ldots, m\}, \forall j; j = \{2, \ldots, n\} \tag{9} \]

\[ A_{ik} \geq T \times \left( 1 - X_{ijk} \right), \forall k; k = \{1,2, \ldots, m\}, \forall i; i = \{1,2, \ldots, n\} \tag{10} \]

\[ A_{ik} + R_i \leq TW_{\text{max}}, \forall k; k = \{1,2, \ldots, m\}, \forall i; i = \{1,2, \ldots, n\} \tag{11} \]

\[ D_{ijk} \geq A_{ik} + R_i \leq T \times \left( 1 - X_{ijk} \right), \forall k; k = \{1,2, \ldots, m\}, \forall i; i = \{1,2, \ldots, n\} \tag{12} \]

\[ E_k - A_{ik} \leq T \max, \forall k; k = \{1,2, \ldots, m\}, \forall j; j = \{2, \ldots, n\} \tag{13} \]

\[ x_{ijk}, Y_{ik} \in \{0,1\}, \forall k; k = \{1,2, \ldots, m\}, \forall j; j = \{2, \ldots, n\} \tag{14} \]

The objective of the model is to maximize tourist satisfaction from attraction scores as shown in equation (1). Constraints (2) and (3) state that there should be no more than one visit at tourist attraction i and j, respectively. Constraints (4) and (5) ensure the connection point between decision variable \( X_{ijk} \) and \( Y_{ik} \). Constraints (6) and (7) ensure that the travelling trip on day \( k \) returns to the starting point. Constraint (8) ensures the continuity of the travelling trip on day \( k \). Constraint (9) guarantees that the sub-tour is eliminated. Constraint (10) states that the travelling trip is arranged within the limit budget. Constraint (11) states that an arrival time at any attraction must be in time window. Constraints (12) and (13) guarantee that the visiting time at each attraction must be within time window. Constraint (14) states that the departure time from an attraction must equal to or greater than its arrival time plus visiting time. Constraint (15) determine the starting time of a travelling trip on day \( k \). Constraints (16) and (17) ensure that the departure time from the last visited attraction must be less than the end travelling time on day \( k \). Constraint (18) ensures that the travelling time on day \( k \) is completed within maximum time horizon. Constraints (19) state that decision variables \( X_{ijk} \) and \( Y_{ik} \) are binary.

3. Application of GLNPSO with swap strategy

The original PSO algorithm was proposed by Kennedy and Eberhart in 1995 [11] in which its concept is originated from the schooling behavior of fish or flocking behavior of birds. The key concept of PSO is that each particle learns from the cognitive knowledge of its experiences (personal best, \( p_{best} \)) and the social knowledge of the swarm (global best, \( g_{best} \)) to guide the particle to better position. Several variants of PSO have been proposed to improve the performances of the original PSO. This study applies an extension of PSO, named GLNPSO, to solve the TTDP. Different from original PSO, GLNPSO, proposed by Pongchairerks and Kachitvichyanukul [12], incorporates multiple social learning terms.
instead of using only single global knowledge. In particular, two additional social learning terms which are local best (lbest) and near neighbor best (nbest) are added in order to enlarge the search space and thus enhance the search efficiency. To increase exploitation capability, this study includes a local search technique called “swap” to intensify the search after some good solutions are found. The framework of GLNPSO with swap strategy is illustrated in Figure 1.

The framework of GLNPSO with swap strategy is developed to deal with multi-objective tourist trip design problem (MO-TTDP). The objective is to find tourist routing that simultaneously maximize tourist satisfaction and minimize total traveling cost. In this framework, solutions are expressed as a set of non-dominated solutions in which several routings are obtained under different budget. Consequently, decision alternatives are provided to tourists, and they can choose an option that best suits their goal.

For the encoding procedures, this study starts from defining the number of particle dimensions to be equal to number of attractions plus twice as much as the number of accommodation. Consider an example with one hotel and nine attractions. The dimensions of a particle are set to be 11 (9 + (2*1)). Each value in a vector dimension is initially generated with a uniform random number between 0 and 1. The dimensions of a vector are divided into two main parts; an accommodation part (dimension value is always equal to 0) and attraction part, as shown in Figure 2. To decode a particle dimension into a routing, a sorting list rule is applied to the attraction part to obtain a sequence of visiting. As shown in Figure 2, the travelling route is determined according to the order of sorted values in a particle dimension. The visiting at each attraction is examined against its time window and time horizon constraints. If the time window or time horizon constraint are violated, the next attraction will be considered. This process continues until a trip return to the accommodation.

![Figure 1. Framework of GLNPSO with swap strategy.](image-url)
This study implements swap technique to intensify the search once the swarm discovers some good solutions. The swap operation is applied when a specific number of iterations is met. Three swap strategies are proposed in this study and the explanation of each strategy are provided as follows.

**Swap1**: The idea of swap1 strategy is to exchange the position of attractions within one day trip. There are three possibilities that can occur which are 1) swapping between unvisited attractions, 2) swapping between visited attraction and unvisited attraction, and 3) swapping between visited attractions. The example of swap1 strategy is illustrated in Figure 3.

**Swap2**: Swap2 strategy is applied when a tourist plans to have two or more travelling days. This strategy exchanges the position of attractions from different travelling days. Similar to swap1, three possibilities; 1) swapping between unvisited attractions, 2) swapping between visited attraction, and unvisited attraction, and 3) swapping between visited attractions can occur in this case. The example of swap2 strategy is illustrated in Figure 4.

**Swap3**: Similar to swap2 strategy, swap3 is applied when a tourist plans to have two or more travelling days. However, swap3 combines the idea of swap1 and swap2 in which the attractions can be exchanged within the same travelling day and different travelling days. The example of swap3 strategy is illustrated in Figure 5.
4. Experimental Results

4.1. Numerical Experiments

In this study, 10 problems are generated based on the real case study in Chiang Mai city, Thailand, for both single tour and multiple tours. The performances of GLNPSO with swap strategy are evaluated and compared with solutions obtained from LINGO optimization program and original GLNPSO. Table 1 show the comparison results when a tourist traveling by a local taxi which is one of the most popular transportation modes in Chiang Mai. It is noted that the objective values obtained LINGO are maximize tourist satisfaction.

| Instance | LINGO | GLNPSO no swap | GLNPSO with swap1 | GLNPSO with swap2 | GLNPSO with swap3 |
|----------|-------|----------------|------------------|------------------|------------------|
| 1        | 21    | (21,120) (17,100) | (21,120) (17,100) | (21,120) (17,100) | (21,120) (17,100) |
| 2        | 21.5  | (21.5,420) (21.2,120) | (21.5,420) (21.2,120) | (21.5,420) (21.2,120) | (21.5,420) (21.2,120) |
| 3        | 30    | (30,1040) (29,600) | (30,1040) (29,600) | (30,1040) (29,600) | (30,1040) (29,600) |
| 4        | 38    | (38,2400) (24,2370) | (38,2400) (24,2370) | (38,2400) (24,2370) | (38,2400) (24,2370) |
| 5        | NA    | (46.5,1270) (46.710) | (46.5,1270) (46.710) | (46.5,1270) (46.710) | (46.5,1270) (46.710) |
| 6        | NA    | (46.5,2270) (46.700) | (46.5,2270) (46.700) | (46.5,2270) (46.700) | (46.5,2270) (46.700) |
| 7        | NA    | (60,3770) (59.5,2270) | (60,3770) (59.5,2270) | (60,3770) (59.5,2270) | (60,3770) (59.5,2270) |
| 8        | NA    | (77,3840) (76.5,1560) | (77,3840) (76.5,1560) | (77,3840) (76.5,1560) | (77,3840) (76.5,1560) |
| 9        | NA    | (93.5,6370) (93.5,6370) | (93.5,6370) (93.5,6370) | (93.5,6370) (93.5,6370) | (93.5,6370) (93.5,6370) |
| 10       | NA    | (98,4940) (96.5,4380) | (98,4940) (96.5,4380) | (98,4940) (96.5,4380) | (98,4940) (96.5,4380) |

Table 1. The result comparison between GLNPSO with swap strategy and LINGO
It can be seen from Table 1 that all PSO algorithms are able to find optimal solutions of maximizing tourist satisfaction when compared with those from LINGO in all small-size problems (Instance 1-4). Additionally, the non-dominated solutions obtained from PSO offer a tourist decision alternatives with different travelling cost so that a tourist can select any solution that best suits their needs. When the problem size increases, while LINGO cannot find solution within a reasonable time, PSO algorithms are capable to provide a set of non-dominated solutions.

5. Conclusion
This research focuses on multi-objective tourist trip design problem (MO-TTDP). The goal is to design optimal tourist routing under time window and time horizon constraints with objectives to simultaneously maximize tourist satisfaction and minimize total traveling cost. The problem is first mathematically formulated as a mixed-integer programming model (MIP). Then, GLNPSO with swap strategy is applied since MIP cannot find optimal solution when the problem becomes more complex. The proposed algorithm is implemented on the real-case studies in Chiang Mai City, Thailand. The results show that the proposed algorithm is capable to yield good solution quality in all cases. Thus, this research can be used as an alternative approach to help tourists with better decision making in designing their trips under budget and time constraints. The future research includes extending the problem with more practical constraints or improving the algorithm performances by incorporating some strategies to better balance exploration and exploitation ability of the search.

6. References

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