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HYBRID EXPERT-TRAVELER PREFERENCES-BASED ANALYTIC HIERARCHY PROCESS FOR OPTIMAL CUSTOMIZED ITINERARY

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Abstract. *Planning itinerary is not an easy matter. It takes a number of skills, such as collecting information on tourist attractions, budgeting, and time scheduling. It is also time-consuming for both travel agents and independent travelers. In this study, we design an optimal customized itinerary which can assist them in arranging a structured and systematic itinerary by using combination of the hybrid expert-traveler preferences-based Analytic Hierarchy Process (AHP) method and the Mixed Integer Programming (MIP) model with the Adaptive Tabu Search (ATS) algorithm. We implement this proposed design to arrange the optimal customized itinerary for a traveler who wants to travel to Bali, Indonesia. Due to constraints of a travel cost, a time limit and his preferences, this traveler who chooses to depart from Pandawa Beach can only visit four of thirty potential attractions in Bali by the optimal route Pandawa Beach – Besakih Temple – Benoa Water Sport – Garuda Wisnu Kencana (GWK) Cultural Park – Pandawa Beach.*
Keywords: Itinerary, Profitable Tour Problems with Priority Prizes (PTPPP), Mixed Integer Programming (MIP), Analytic Hierarchy Process (AHP)

1. **Introduction.** Traveling is the activity of making journeys or travel. On traveling, we need a travel itinerary to determine the visit of tourist attractions and carry out activities that have been scheduled during the visit. Da Silva et al. defined a travel itinerary as a planned itinerary of a tourist activity such as attractions, the sequence of activities, and duration [1].

The growth of the tourism sector is marked by the emergence of many travel agencies in almost every tourist attraction. However, the various itineraries on offer often do not fully suit the interests of the travelers. Meanwhile, independently designing travel itinerary can be time-consuming and requires special skills in budgeting. Planning itinerary is not just a matter of how to model the right route choice [2, 3, 4], but also needs to optimize the satisfaction of travelers and the cost of the itinerary. Therefore, we need a methodology to assist travelers in designing optimal customized itineraries.

The optimal itinerary problem is usually solved according to several reward metrics [5, 6, 7] by emphasizing the data mining aspects of planning itinerary. This problem can be categorized as a Traveling Salesman Problem (TSP). The TSP is one of the most comprehensively studied problems which is divided into two types, i.e., the TSP with Profits (the Profitable Tour Problem or PTP) [8, 9, 10], and the TSP with Priority Prizes (TSPPP) [11]. The combination of these two types is called as the Profitable Tour Problems with Priority Prizes (PTPPP). The objective of the PTPPP is to maximize the preferences of the places to be visited and traveler satisfaction and all at once to minimize the itinerary cost. In the previous studies, the PTPPP is solved by metaheuristic approach, i.e., the Tabu Search (TS) algorithm [12, 13]. The TS algorithm is suitable in

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the various real situations to treat large instances of the PTPPP. However, there are a lot of tunable parameters in this algorithm and it has very high number of iterations such that it needs long computational times.

In this study, we follow Da Silva et al. [1] in representing the PTPPP as a Mixed Integer Programming (MIP) model with Adaptive Tabu Search (ATS) algorithm [14, 15] in relatively short computational times. However, we still need objective input parameters of the PTPPP which represent a customized itinerary according to the traveler preferences. The traveler's ignorance of the tourist attractions to be visited is accommodated by an assessment of tourism experts who have visited each of tourist attractions in each destination. The Analytic Hierarchy Process (AHP) method [16] can help us to meet this need in a structured and systematic manner by comparing many potential tourist attractions numerically based on some criteria to reach traveler satisfaction. The novelty of this study is that we construct a framework of the AHP method based on the preferences of the traveler and the recommendations of tourism experts on the tourist attractions where the priority results obtained are then used as input parameters of the PTPPP. Thus, each traveler will have an itinerary according to their respective preferences.

The rest of the paper is organized as follows. In Section 2, we describe the MIP model with ATS algorithm for the PTPPP. Section 3 generally describes the proposed framework of the AHP method for customized itinerary. The implementation stages of the proposed design of optimal customized itinerary and its computational results are discussed in Section 4. Finally, in Section 5 we present the conclusion and future works.

2. **The MIP Model with the ATS Algorithm for the PTPPP.** As mentioned earlier in Section 1, the PTPPP can be formulated as an MIP model by first representing the problem as a directed graph $G(N, A)$, where $N = \{1, 2, \ldots, n\}$ denotes the set of tourist attraction nodes (including hotel which is considered as the first node $i = 1$, $i \in N$). Meanwhile, $A = \{(i, j) : i, j \in N, i \neq j\}$ denotes a set of arcs that can be formed from two different vertices on N [1]. Suppose given parameters as follows:

p_{ki}: Valuation (priority prize) of the traveler visiting attraction $i \in N$ in order k;

p_i: Valuation (visit prize) given by traveler when visiting attraction $i \in N$;

c_{ij}: Travel cost of $\text{arc}(i, j) \in A$.

In addition, define the following decision variables:

$$x_{ij} = \begin{cases} 1 & \text{if arc}(i, j) \in A \text{ is traveled,} \\ 0 & \text{otherwise.} \end{cases}$$

$$y_{ki} = \begin{cases} 1 & \text{if } i \in N \text{ is visited in order } k\,(1 \leq k \leq n) \text{ of the itinerary,} \\ 0 & \text{otherwise.} \end{cases}$$

z_i: Auxiliary unconstrained variable to avoid sub-cycles in the route ($i \in N$), as known as Miller-Tucker-Zemlin (MTZ) condition.

Thus, the MIP model for PTPPP problems can be expressed as follows [1]:

$$\max f = \sum_{k}^{n} \sum_{i}^{n} (p_{ki} + p_i)\, y_{ki} - \sum_{(i,j) \in A} c_{ij} x_{ij}, \tag{1}$$

$$\sum_{(i,1) \in A} x_{i1} = 1, \tag{2}$$

$$\sum_{(i,j) \in A} x_{ij} = \sum_{k=1}^{n} y_{kj}, \ \ j \in N, \tag{3}$$

$$\sum_{(1,j) \in A} x_{1j} = 1, \tag{4}$$

$$\sum_{(i,j)\in A} x_{ij} = \sum_{k=1}^{n} y_{ki},\ i \in N, \tag{5}$$

$$z_i - z_j + n x_{ij} \leq n-1,\ (i,j) \in A,\ i \neq 1, \tag{6}$$

$$x_{1j} = y_{1j},\ j \in N, \tag{7}$$

$$x_{ij} \geq y_{(k-1),i} + y_{kj} - 1,\ (i,j) \in A,\ 1 < k \leq n, \tag{8}$$

$$\sum_{i=1}^{n} y_{ki} \geq \sum_{j=1}^{n} y_{k+1,j},\ 1 \leq k < n, \tag{9}$$

$$\sum_{k=1}^{n} y_{ki} \leq 1,\ i \in N, \tag{10}$$

$$\sum_{i=1}^{n} y_{ki} \leq 1,\ 1 \leq k \leq n, \tag{11}$$

$$x_{ij}, y_{ki} \in \{0,1\},\ i \in N,\ (i,j) \in A,\ 1 \leq k \leq n. \tag{12}$$

The objective function (1) is not only maximizing the prizes in visiting the attraction and its order, but also simultaneously minimizing the travel costs. The assignment constraints of decision variable x are represented in Equations (2), (3), (4) and (5), which are also pair of decision variables x and y. Equations (2) and (4) guarantee that the itinerary always returns to the place of origin. If a tourist attraction is visited, it is only visited once as in Equations (3) and (5). The MTZ constraint [17] is given in Equation (6). Equations (7) and (8) define the order of each of visited attractions in the itinerary. Equation (9) ensures that the first orders attractions will be assigned to the visited attractions of the itinerary. Equation (10) also ensures that each attraction is not visited more than once, while Equation (11) reinforces that each order is not used more than once. They refer to assignment constraints of decision variable y. The domain of the decision variables is defined in Equation (12). This model is then solved by ATS algorithm [14, 15]. The complexity of this algorithm can be read in detail in Xia et al. [15].

In this study, the MIP model with the ATS algorithm for the PTPPP is performed on python programming. The input parameters in this model, i.e., priority prizes and visit prizes, are defined as a function of traveler preferences and tourism experts assessment refers to the priority attractions results of the proposed AHP framework as described in Section 3.

3. The Proposed Hybrid Expert-Traveler Preferences-Based AHP Method.

The AHP method as a general theory of measurement is used to obtain ratio scales from both discrete and continuous pairwise comparisons by taking from actual measurements or from a fundamental scale [16]. This principle is used in this study to measure both of the relative strength of traveler preferences and feelings and tourism expert assessment. The AHP method can solve complex multicriteria problems into a hierarchy which is defined as a multi-level structure: objective/goal, decision criteria, sub-criteria and so on down to the last level of the alternatives [18].

Many previous studies that used AHP and its improvement as a method in solving the tourism problems such as in choosing online-base travel agents [19], in measuring tourist preferences of smart tourism attractions via Fuzzy Comprehensive Evaluation Method (FCEM)-AHP [20], in deriving strategic priority of policies for creative tourism industry [21], in analyzing the service quality in digital hospitality industry via fuzzy-AHP [22], in estimating tourist district livability [23], in analyzing coastal tourism sites [24], in analyzing perceptual differences in core competencies between tourism industry practitioners and students [25], in ecotourism suitability via fuzzy-AHP [26], in evaluating the rural ecotourism resource [27], in analyzing the tourism industry employability [28], in selecting a cruise port of call location via fuzzy-AHP [29], etc.

Figure 1 shows the proposed framework of the AHP method for customized itinerary. It consists of four comparison layers. The first comparison layer compares decision criteria based on the objective/goal, i.e., successful destination [30]. We consider three decision criteria which can be used for traveler in determining the priority of tourist attractions to be visited as follows: satisfaction, experience and insight [31]. Based on these three criteria, in the second comparison layer, it will be compared how important the following nine factors are in reaching the goal, i.e., tourist attraction, tourist amenities, accessibility [30, 31, 32, 33, 34], tourist activities [31, 32, 34], accommodation, culinary [31, 34], cost, travel information [33] and popularity [34]. In the third comparison layer, we group tourist attractions into four categories as used by Public Use Planning effort of the World Heritage Center [35], i.e., geophysical-landscape-aesthetic, ecological-biological, cultural-historical and recreational. All of tourist attractions groups are compared each other based on the nine factors in the second comparison layer. Finally, a number of attractions are compared to one another to measure how potential they fit into the categories in the third comparison layer. The travelers enter their preferences into the first two comparison layers while the tourism experts enter their assessment into the last two comparison layers. In this study, we use the fundamental scale values to compare every pair of elements in each layer as in [16].

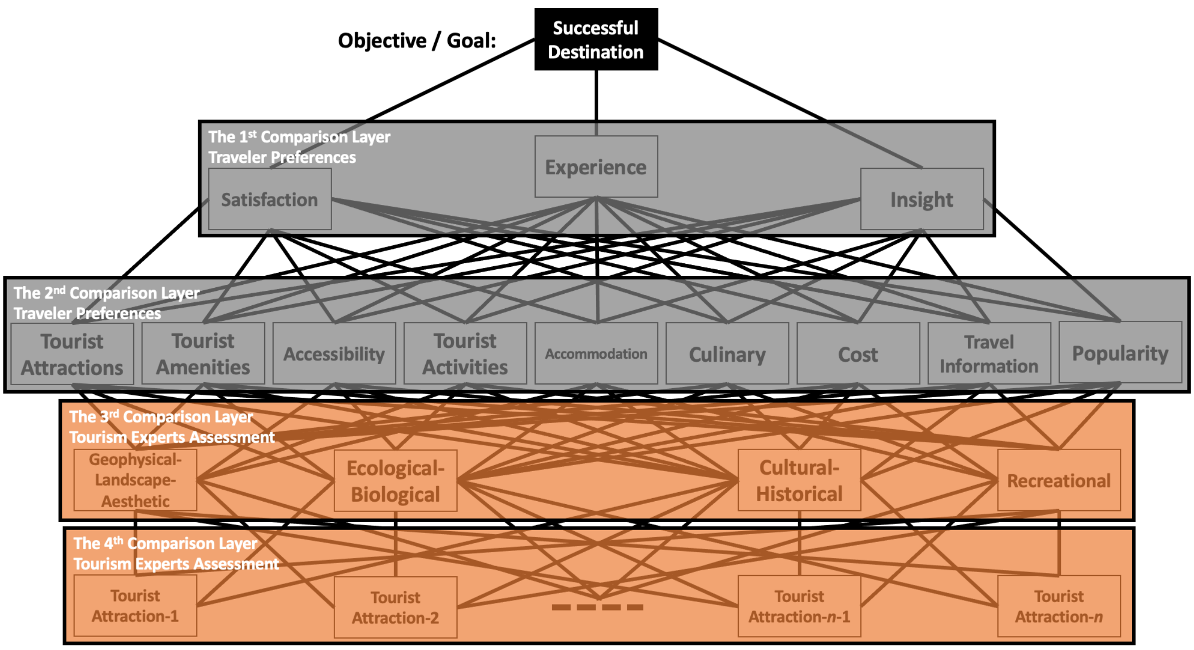

FIGURE 1. The proposed hybrid expert-traveler preferences-based AHP framework

4. **Implementation.** In this study, we implement the proposed design of optimal customized itinerary as described in Sections 2 and 3 using combination of the hybrid expert-traveler preferences-based AHP method and the MIP model with the ATS algorithm for a traveler who wants to travel to Bali, Indonesia. We only choose thirty random potential tourist attractions in Bali as an example to validate the proposed design in arranging recommendation of travel itinerary. The following are the implementation stages of the proposed design of optimal customized itinerary:

Stage 1: The traveler enters his preferences into the first two comparison layers of the proposed AHP framework in Figure 1.

Stage 2: The tourism experts enter their assessment into the last two comparison layers of the proposed AHP framework in Figure 1. Noted that, in this study, we use geometric average to get the final assessment.

Stage 3: Synchronize the comparison values of the proposed AHP framework in Stages 1 and 2 to get the priority attractions results.

Stage 4: Input the parameter values required of the MIP model with the ATS algorithm where both of priority prizes and visit prizes are defined as a function of priority attractions results in Stage 3. Noted that, in this study, we use any piecewise linear function and linear function for priority prizes and visit prizes, respectively.

Stage 5: Optimize the MIP model with the ATS algorithm based on the input parameter values in Stage 4.

As described in Stages 1-3, after the traveler enters his preferences and the tourism experts enter their assessment, the proposed AHP is synchronized to produce the priority attractions as sample shown in Table 1. The priority attractions results, either the ideals or the normals, are on a scale from 0%-100% where the ideals are obtained by dividing all raw values from the limit supermatrix [16] by the largest of them. Meanwhile, the normals are obtained by normalizing all that raw values.

Table 1. Sample priority attractions results of the proposed AHP framework

No.	**Potential attractions**	**Priority**	
		Ideals	**Normals**
1	Pandawa Beach	100	6.05
2	Kuta Beach	52.64	3.19
3	Sanur Beach	57.30	3.47
4	Lovina Beach	62.23	3.77
5	Tegal Wangi Beach	30.47	1.84
6	Seminyak Beach	77.09	4.67
7	Crystal Bay Beach	87.45	5.29
8	Benoa Water Sport	92.04	5.57
9	Dreamland Beach	83.58	5.06
10	Padang Padang Beach	21.27	1.29
11	Legian Beach	2.41	0.15
12	GWK Cultural Park	95.90	5.81
13	Tirta Gangga	46.95	2.84
⋮	⋮	⋮	⋮
30	Uluwatu Temple	83.43	5.05

Table 2 presents the sample input visit prizes, p_i, and travel costs, c_{ij}, of the traveler. The visit prizes values are obtained from the ideal priority attractions results which represent the valuation of travelers when visiting tourist attractions. The travel costs allocated to each pair of these thirty potential attractions come from the taxi rates (in thousands Rupiah) which is taken from the Go-Jek application [36].

Noted that travelers are willing to pay more if some attractions are in the first or last orders of the itinerary [1]. Table 3 presents the input of priority prizes, p_{ki}. Based on the normal priority attractions results on a scale from 0% to 100%, we know the order of the recommended attractions such that we can use these results as an input of priority prizes depending on the traveler preferences whether he wants to visit the most recommended ones at the beginning or at the end of the itinerary. Therefore, we can see in Table 3 that the priority prizes are only in order-1 and order-29.

Based on Table 2 and Table 3, we then optimize the MIP model with the ATS algorithm to get the optimal customized itinerary for this traveler. In this study, we choose Pandawa

TABLE 2. Sample input visit prizes p_i and travel costs c_{ij}

No.	Potential attractions	Visit prizes	Travel costs														
			Pandawa Beach	Kuta Beach	Sanur Beach	Lovina Beach	Tegal Wangi Beach	Seminyak Beach	Crystal Bay Beach	Benoa Water Sport	Dreamland Beach	Padang Padang Beach	Legian Beach	GWK Cultural Park	Tirta Gangga	⋯	Uluwatu Temple
1	Pandawa Beach	100	0	145	98	145	128	130	145	155	90	135	140	151	89	⋯	100
2	Kuta Beach	52.64	140	0	100	120	150	98	90	145	141	100	140	144	150	⋯	155
3	Sanur Beach	57.30	124	85	0	122	113	126	181	178	139	110	156	105	166	⋯	130
4	Lovina Beach	62.23	140	93	170	0	137	161	175	72	188	70	120	149	98	⋯	158
5	Tegal Wangi Beach	30.47	183	159	114	148	0	97	158	71	146	115	174	115	185	⋯	129
6	Seminyak Beach	77.09	116	71	118	183	140	0	127	162	138	76	154	97	94	⋯	82
7	Crystal Bay Beach	87.45	122	71	92	71	124	139	0	94	79	188	170	166	124	⋯	147
8	Benoa Water Sport	92.04	130	134	152	90	77	164	123	0	133	98	132	87	187	⋯	116
9	Dreamland Beach	83.58	153	161	118	175	174	149	71	154	0	118	83	161	85	⋯	115
10	Padang Padang Beach	21.27	92	132	165	131	174	172	117	78	78	0	97	129	188	⋯	78
11	Legian Beach	2.41	132	137	168	172	121	188	140	121	155	173	0	108	98	⋯	80
12	GWK Cultural Park	95.90	107	162	176	110	159	152	126	82	186	135	135	0	155	⋯	132
13	Tirta Gangga	46.95	151	135	189	75	158	104	189	149	146	96	124	96	0	⋯	104
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮
30	Uluwatu Temple	83.43	130	130	125	123	170	175	115	141	129	99	85	71	114	⋯	0

TABLE 3. Sample input priority prizes p_{ki}

Order k	Priority prizes														
	Pandawa Beach	Kuta Beach	Sanur Beach	Lovina Beach	Tegal Wangi Beach	Seminyak Beach	Crystal Bay Beach	Benoa Water Sport	Dreamland Beach	Padang Padang Beach	Legian Beach	GWK Cultural Park	Tirta Gangga	⋯	Uluwatu Temple
1	0	3.19	3.47	3.77	1.84	4.67	5.29	5.57	5.06	1.29	0.15	5.81	2.84	⋯	5.05
2	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮
27	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0
29	0	5.05	4.67	3.77	5.29	3.47	1.84	1.29	2.84	5.57	5.81	0.15	5.06	⋯	3.19
30	0	0	0	0	0	0	0	0	0	0	0	0	0	⋯	0

Beach as a starting point because it has the highest ideal priority attractions (100%). Due to constraints of a travel cost and a time limit, finally, he can only visit four of thirty potential attractions in Bali by the optimal route Pandawa Beach – Besakih Temple – Benoa Water Sport – Garuda Wisnu Kencana (GWK) Cultural Park – Pandawa Beach.

5. **Conclusions.** The optimal customized itinerary is important in the tourism industry. It not only helps travel agencies in arranging the optimal itinerary for each of their customers, but also helps the traveler to get the satisfying itinerary that suits their preferences. We have designed an optimal customized itinerary by inserting the proposed hybrid expert-traveler preferences-based AHP results to the input parameters of the PTPPP that is solved by the MIP model with the ATS algorithm. The proposed framework of the AHP method consists of four comparison layers: three decision criteria in the first layer for successful destination as an objective/goal, i.e., tourist attraction, tourist amenities, accessibility, tourist activities, accommodation, culinary, cost, travel information and popularity; four categories of attractions in the third layer, i.e., geophysical-landscape-aesthetic, ecological-biological, cultural-historical and recreational; and a number of attractions for one destination in the last layer. The travelers input their preferences into the first two comparison layers while the tourism experts input their assessment into the last two comparison layers. It has been implemented to arrange the optimal customized itinerary for a traveler who wants to travel to Bali, Indonesia. Due to constraints of a travel cost and a time limit, if he departs from Pandawa Beach then he can only visit four of thirty attractions in Bali by the optimal route Pandawa Beach – Besakih Temple – Benoa Water Sport – Garuda Wisnu Kencana (GWK) Cultural Park – Pandawa

Beach. In the future work, we will build an application for travel agencies to collect the characteristics of traveler preferences massively based on the optimal customized itinerary design. By combining the collected data with other related open tourism data, the deep learning approach can be implemented to improve this design for further research. Moreover, the high-performance computing can be performed in the optimization problem to obtain better computational performance as the data size increases. Several parameters can also be added into the PTPPP, e.g., number of travelers, and range of ages, so that the optimal customized itinerary can be enriched to be more representative.

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