Multi Attributes Approach for Tourist Trips Design

Ilaria Baffo[1], Pasquale Carotenuto[2], Antonella Petrillo[3], Fabio De Felice[4]

[1] Industrial Engineering School (DEIM) - University of Tuscia, Italy
ilaria.baffo@unitus.it
[2]Istituto per le Applicazioni del Calcolo (IAC) - CNR, Italy
p.carotenuto@iac.cnr.it
[3]Department of Engineering - University of Naples "Parthenope", Italy
antonella.petrillo@uniparthenope.it
[4]Department of Civil and Mechanical Engineering - University of Cassino and Southern Lazio, Italy
defelice@unicas.it

Abstract. The authors propose a Multi Attributes approach to meet the demand of personalized tourist tours into cultural cities. Respecting to others works present into the literature, in this paper the decisional process includes two phases and a high number of variables that don't increase the complexity of the problem. A real application in an Italian city, Florence, is presented to demonstrate the great potential of this system into real context. The first phase of optimization is solved applying an innovative Genetic Algorithm, the second one a Multi Criteria Method, Analytic Hierarchy Process (AHP). The combination of these two approach gives flexibility to the system with respect to number of variables and allow to return a good solution for tourist in few second of computational time.

1   Introduction

The increasing use of mobile devices in everyday life has favored the creation of intelligent applications also in field such as tourism, culture and hobbies. One of the most interesting applications provides opportunity to help tourists in choosing the best route given a maximum time of visit. During the last years several researchers have faced this problem with the aim to reduce uncertainty and increase the personalization of the tourist paths. In the scientific literature, the problem is better known as Tourist Trip Design Problem (TTDP). The authors in this work propose a Multi Attributes Decision Support System (MDSS) to meet the demand of personalized tourist tours into cultural cities. As described in the following many researchers have successfully addressed this problem, but, only few of these have proposed real applications able to consider several attribute to decisional process. The Multi Attributes Decision Support System proposed, facing the TDPP in two steps. Firstly, a Genetic Algorithm (GA) solves in optimal way the Orienteering Problem (OP) on real instances coming from Italian historical cities, Florence. The validation of algorithm is guaranteed creating an A Mathematical Programming Language (AMPL) model able to return the optimal solution for small instances of the same problem. Finally, the optimal solutions are compared on basis of different attributes having the features to be added

up. The last step has been conducted with the use of Multi Criteria Analysis Methods. Thank to this approach, the obtained solutions can be evaluated on basis of several *attributes* like: time of decision with respect to time of travel, duration of travel, levels of freedom into the decision, degree of additionality of preferences, number of decision-makers, numbers of cultural heritages to visit, etc. Real cases studies are given with the aim to offer development ideas for implementation of smart applications for tourist trips' design. The proposed methods can reach important results where the variables of the problem are numerous and the optimization process too long and complex. The rest of paper is organized as follows: a review of literature is given in section 2, the mathematical model and its resolution with genetic algorithm is explained in section 3. Section 4 presents AHP approach and its integration with optimization model is discussed. Application and results are analyzed in Section 5. Finally, conclusion and future researches are proposed in section 6.

2   Literature Review

As well explained in [5,10] the described route-planning problem has been considered as an application of the Orienteering Problem or its variants. In the OP, several locations with an associated score have to be visited only once in order to obtain a total trip score. The objective is to obtain a total trip score as high as possible without violating a time restriction. There have been works on exact methods that have yielded solutions to smaller sized problems. Due to the computational limitations of the exact algorithms, several heuristic were explored to many researchers in the past. The first heuristics were proposed by Tsiligirides (1984) in [9] and are known as the S-algorithm and the D-algorithm. The S-algorithm uses the Monte Carlo method to construct routes using probabilities correlated to the ratio between node score and node distance from the current node. The D-algorithm is built based upon the vehicle scheduling method proposed by Wren and Holiday (1972) [12]. Others heuristics have been explored in the years to solve this kind of problems, in [8] a Tabu Search approach has been used for Multi Constrained Team Orienteering Problem and its application in touristic trip planning. In [7,11] the authors propose to solve the Multi–Constraint Team Orienteering Problem with Multiple Time Windows with known heuristic like Iterated Local Search (ILS) and Greedy randomized adaptive search procedure (GRASP). Iterated Local Search is proposed also in [4] to solve real-time Time Dependent Team Orienteering Problem with Time Windows (TDTOPTW). During the last years, many authors have chosen to implement evolutionary algorithm trying to reduce the computational time and to improve the quality of proposed solution to tourist. In [2] the authors propose an evolutionary algorithm to solve a multi-objective problem for personalized tours in street networks. In this case, the trip is long multiple–day and a Team Orienteering Problem with Time Windows (TOPTW) is solved with a heuristic approach whose computational times are not clearly declared. The aim of the authors is to give in few second an optimal solution of OP and secondly introduce more elements that can be analyzed with multi criteria analysis. In this way, the complexity of the problem is lower and the computational time too, then the approach is more usable for real time digital applications.

3 Problem Description

In this work the authors face the single day Tourist Trip Design Problem (TTDP) modelling an Orienteering Problem (OP). In the OP, a set of *N* location, also called Point of Interest (PoI*s*), corresponding with nodes *i* is given, each with a score S_i. The starting point and the end point are fixed. The time t_{ij} needed to travel from vertex *i* to *j* is known for all vertices. The problem became more complex because not all the vertices can be visited since a given threshold T_{max} limits the available time. The goal of the OP is to determine a path, limited by T_{max} that visits some of the vertices, in order to maximize the total collected score. Other works propose to optimize the problem maximizing the number of PoI*s* visited, the problems coincide if we suppose each point's score equal to 1. The scores are assumed to be entirely additive and each vertex can be visited at most once. In this algorithm the maximum time available to visit the PoI*s* is considered as constrain of the problem. At the same time, all solutions are defined by a set of PoI*s* visited, a time of visit for each point and a time of walking from one point to another point. The OP can be formulated as follows: $S_i \geq 0$ is the score associated to node *i*, c_{ij} is the cost associated to path between node *i* and node *j*. Usually *n* nodes are considered in the Euclidean plane. Since the distance and travel time between nodes are determined by the geographical measure, distance is used as the representative of path's cost. Generally, the mathematical model of the OP is formulated as follows:

$$MAX \sum_{i=1}^{n} \sum_{j=1}^{n} S_i\, x_{ij} \tag{1}$$

Subject to

$$\sum_{j=2}^{n} x_{1j} = \sum_{i=1}^{n-1} x_{in} = 1 \tag{2}$$

$$\sum_{i=2}^{n-1} x_{ik} = \sum_{j=2}^{n} x_{kj} \leq 1 \qquad k=2,\ldots,n-1 \tag{3}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \leq T_{max} \qquad \forall i, j=1,\ldots,n \tag{4}$$

$$2 \leq u_i \leq n \qquad \forall\, i = 1,\ldots,n \tag{5}$$

$$u_i - u_j + 1 \leq (n-1)(1-x_{ij}) \qquad \forall\, i,j= 1,\ldots,n \tag{6}$$

$$x_{ij} \in \{0,1\} \qquad \forall\, i,j= 1,\ldots,n \tag{7}$$

Where (1) represents the problem's Objective Function to maximize the total collected score S. Constraint (2) guarantee that the path starts in vertex 1 and ends in vertex N. Constraint (3) ensures the connectivity of the path and guarantee that every vertex is visited at most once. Constraint (4) ensures the limited time budget T.

Constraints (5) and (6) are necessary to prevent sub-tours. Constraints (7) requires that the variables are binary. The decisional variable x_{ij} is equal to 1 if the node j to i are connected, 0 else. This formulation guarantees as result a tour able to: Visit as many PoIs as possible; Visit PoIs at most once; Visit PoIs that maximize the Total Score (Objective Function); Visit PoIs connected among them; and Visit PoIs respecting the limitation time. The set of solutions coming from the genetic algorithm represent the inputs for multi criteria approach with AHP.

4   Multi criteria approach: Analytic Hierarchy Process.

The AHP breaks down a decision-making problem into several levels in such a way that they form a hierarchy with unidirectional hierarchical relationships between levels [3]. The AHP for decision making uses objective mathematics to process the inescapably subjective and personal preferences of an individual or a group in making a decision. With the AHP, one constructs hierarchies or feedback networks, then makes judgments or performs measurements on pairs of elements with respect to a controlling element to derive ratio scales that are then synthesized throughout the structure to select the best alternative. The top level of the hierarchy is the main goal of the decision problem. The lower levels are the tangible and/or intangible criteria that contribute to the goal. The bottom level is formed by the alternatives to evaluate in terms of the criteria. The modeling process requires a *pairwise comparison*s of the elements in each level using a scale of 1-9, as suggested by Saaty [6]. The result of the comparison is the so-called dominance coefficient a_{ij} that represents the relative importance of the component on row (i) over the component on column (j), i.e., $a_{ij}=w_i/w_j$. The pairwise comparisons can be represented in the form of a matrix. After all pairwise comparison is completed, the priority weight vector (w) is computed as the unique solution of $Aw=\lambda_{max}w$, where λ_{max} is the largest eigenvalue of matrix A. Finally, consistency index CI is estimated. CI could then be calculated by: $CI=(\lambda_{max}-n)/n-1$. In general, if *CI* is less than 0.10, satisfaction of judgments may be derived. For this application the AHP takes as input the results of optimization process and evaluates these under several criteria better explained in the next paragraph. As first activity, the mathematical model is supposed to model the capacitated orienteering problem, as second phase we solve the formulation implemented a meta-heuristic known as Genetic Algorithm (GA). Then, we applied a multi-criteria analysis (AHP model) to algorithm's results to order the founded solutions respect to the following objectives: Time L-path, Visited places, Ticket cost.

5   Problem Resolution

The authors propose an optimization approach that draw inspiration on Genetic Algorithm (GA) as developed by Holland (1975) and then described by Goldberg (1989). GA starts initializing a First Population composed by a pre-determinate number of individuals. Each individual represents a solution for the faced problem and it is characterized by several elements such a chromosome and a fitness value.

The individual's chromosome is composed by several gene that can assume binary or integer value, the combination of these genes usually represents the problem's solution thanks to a correspondence between the gene's value and the problem's variables value. The individual's fitness value corresponds to solution objective function's value, and it's basic into determinate the individual's probability to survive at evolution process, so that bad individuals are destined to not have a long life into population. The difference between the old and the new population in the evolutionary process is guaranteed by the presence of two important operations called Mutation and Crossover. After several generations, the best solution converges, and it hopefully represents the optimum or suboptimum solution to the problem at hand. GA are successfully applied to different contexts in order to solve a very large number of problems, for this purpose various and original genetic operators are developed, that revisit the original concept of mutation and crossover. In this application the authors adopt a circular representation of chromosome and several heuristic techniques to improve the evolutionary process through mutation and crossover operations. In our GA the chromosome is composed of all nodes that the tourist want visit, without the start node and the end node that can be added at the end of optimization process. This coding of chromosome with respect to problem's solution representing by a single tour, allows to have only admissible solutions better or worst on basis of Total score reached by visiting more or more better PoI*s*. The Fig. 1 shows like each chromosome represents a sequence of visiting PoI*s*, i.e. a tour, i.e. a solution for the OP. The Closed loop Structure of Chromosome code allows a wider and faster research of solutions.
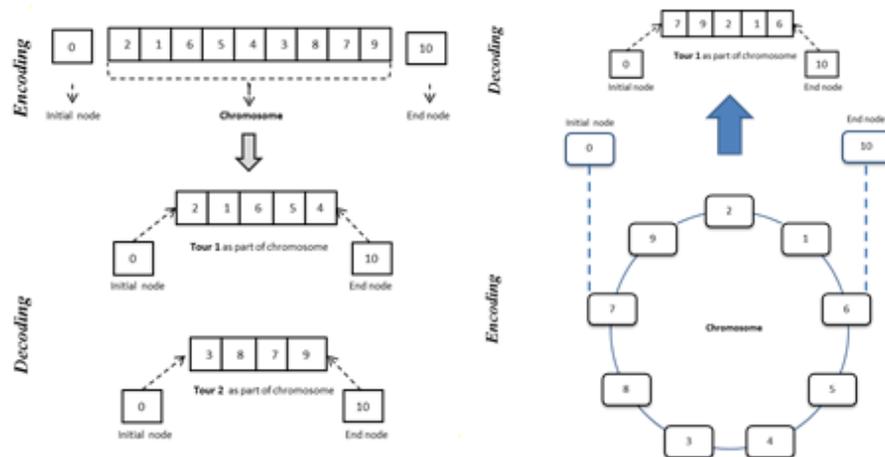
Fig. 1: Encoding and Decoding process

As previously described the GA structure is based on constitution of a population at each iteration. This population step by step evolves and the algorithm found better solutions for the faced problem. Following a synthetic description of the implemented GA pseudocode is reported.

```
Parameters Setting
Initialization
   Generate a feasible solution randomly as individual
```

```
   Save them into the population Pop (i)
   Loop until the population's size S is reached
   Calculate Fitness to define the Best Individual BI(i) of P(i)
   While the number of iterations isn't reached do
Set iteration i = 0
   Selection: Roulette function for selecting two individual as parent
   Crossover (Single, PMX)
   Evaluate Fitness
   Update the Best individual when offspring is better than actual Best
   Individual BI(i)
   Mutation (Smart Swap)
   Evaluate Fitness
   Update the best individual when offspring is better than actual Best
   Individual BI(i)
Build
   Build new Population Pop (i+1) as collection of individuals generated
   with Crossover and Mutations Operations
Next i
End - Return the best individual containing the best tour
```

More details are given into a previous publication of authors in [1]. The solutions given by optimization process constitute inputs for Multi Criteria Analysis Approach. Finally, the Multi Attributes Approach for Tourist Trips Design Problem (MATTDP) gives as output a solution that takes into account a lot of variables, some of these are considered into optimization process and others into Multi Criteria Analysis Process.

5.1   Real Application

In this paragraph, we propose the results obtained for the single-day Tourist Trip Design Problem (TTDP) in the city of Florence. We consider 24 PoIs, all included into urban areas of the city. We fix the PoIs of departures and of arrival and the maximum time that the tourist has to visit the city, variable from 390 minutes to 930 minutes. We calculated the distance matrix and set the algorithm parameters (numbers of individuals, population and Best Solution Containers's (BSC) size, Frequency rate of genetic operators) on the basis of preliminary tests that have given the best configuration of algorithm. For each PoI, we suppose that the tourist assigns a different score on the basis of your preference. The Total time of tourist path is calculated as summarize between the time to reach the PoI and the time to visit it that it is supposed to be equal to 30 min for each one. The Table 2 presents the results coming from the optimization process; the authors found 5 solutions/tours (called 1, 2, 3, 4, 5) for 5 different time each one starting from PoI 1 and ending to PoI 24. Each PoI is represented by a number from 1 to 24 and each Tour can be considered as a sequence of visited PoIs. As showed in Table 1 for each solution a Real time of tour, a total time of tour, a total score of tour and the number of visited PoIs are given. T_{max} real is expressed in minutes like Time for visit the PoIs and the relative Total Time. T_{max} is expressed in a conventional measure used into the algorithm, Total Score and Visited PoIs have no units of measure. For summarizing, each solution coming from optimization process is characterized by a number or a sequence of visited PoIs, and a Total time needed for completing the tour as sum of time to reach all PoIs of tour and time to visit them.

Table 1: Data of solutions

Solutions	1	2	3	4	5
Tmax	5	8	10	15	20
Real Tmax	60	96	120	180	240
Time of visit	330	450	540	660	690
Total time	390	546	660	840	930
Total score	75	110	145	170	185
Visited PoIs	11	15	18	22	23

The outputs of optimization process as before described are given as inputs o**f** AHP model built as in Fig. 2. In the present paper AHP Absolute model is applied as in [**3**].

Table 2: Solutions of optimization

Solutions	Tour
1	1 10 7 18 3 2 5 6 4 23 24
2	1 20 18 12 2 3 10 4 6 5 8 17 22 23 24
3	1 18 12 14 9 3 5 2 6 4 8 17 22 21 23 16 11 24
4	1 14 19 18 12 2 3 10 17 21 22 7 5 6 9 8 4 23 16 11 24
5	1 2 9 6 5 3 7 12 10 18 20 19 22 4 17 8 21 23 16 11 14 24

AHP Absolute model is based on paired comparisons among the elements of a set with respect to a common attribute. Experts team developed pairwise comparison matrices to determine the weights of criteria. Consistency index has been estimated (CI 0.018). Results show that the most important criteria is "C1. Time L_{path}" with a score of 56%, followed by "C3. Ticket cost" with a score of 32%, and finally is the criteria "C2. N° Visited places" with a score of 12%. In AHP Absolute model criteria are further subdivided into a level for intensities. The scores of these intensities are each weighted by the priority of its criterion and summed to derive a total ratio scale score for the alternative. Each criterion has ratings listed under it. Tab. 3 shows the final ranking of the AHP Model.
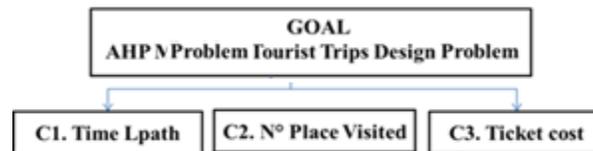
Fig. 2. AHP Absolute Model

	Priorities	C1 Time Lpath	C2 N* Place Visited	C3 Ticket cost
		0.5584	0.1219	0.3196
5	0.3750	0.5 km	11	10-20 €
8	0.2423	1 km	15	20-40 €
10	0.1599	1.5 km	18	40-60 €
15	0.1174	2 km	22	60-80 €
20	0.1052	2.5 km	23	80-90 €

Tab. 3. Final Ranking

6 Conclusions and Future Researches

In this work the authors present a Multi Attributes Approach for solving single-day Tourist Trips Design Problem (MATTDP). The proposed System is applied to a real case into the Italian city of Florence. Thanks to two phases of this approach it is possible to include several variables into the decisional process without increase the complexity of the problem. For future researches, the authors want to implement the system in a big instance of the problem considering also time windows constraints for visiting PoIs. The next step could be to implement a mobile application for smartphone and tablet in order to test the real usability of this system in real context.

References

1. Baffo, I., Carotenuto, P., Storchi, G., A genetic algorithm to design touristic routes in a bike sharing system, 14th international conference on modeling and applied simulation, At Bergeggi (Liguria) – Italy, (2015).
2. De Falco, I., Scafuri, U., & Tarantino, E. A multiobjective evolutionary algorithm for personalized tours in street networks. In European Conference on the Applications of Evolutionary Computation. Springer International Publishing. (2015) 115-127.
3. De Felice F., Petrillo A., Absolute measurement with analytic hierarchy process: A case study for Italian racecourse. International Journal of Applied Decision Sciences. Volume 6, Issue 3, 2013, (2013) 209-227.
4. Garcia, A., Arbelaitz, O., Linaza, M. T., Vansteenwegen, P., & Souffriau, W. Personalized tourist route generation. In International Conference on Web Engineering. Springer Berlin Heidelberg. (2010) 486-497.
5. Gavalas, D., Konstantopoulos, C., Mastakas, K., & Pantziou, G. A survey on algorithmic approaches for solving tourist trip design problems. Journal of Heuristics, 20(3), (2014) 291-328.
6. Saaty, T.L., (1977. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 15, 234–281.
7. Souffriau, W., Vansteenwegen, P., Vanden Berghe, G., & Van Oudheusden, D. The multiconstraint team orienteering problem with multiple time windows. Transportation Science, 47(1), (2013), 53-63.
8. Sylejmani, K., Dorn, J., & Musliu, N. A tabu search approach for multi constrained team orienteering problem and its application in touristic trip planning. In Hybrid Intelligent Systems (HIS), 12th International Conference on IEEE. (2012) 300-305.
9. Tsiligirides, T., Heuristic Methods Applied to Orienteering. Journal of Operational Research Society, vol. 35, no. 9, (1984) 797-809.
10. Vansteenwegen, P., Souffriau, W., & Van Oudheusden, D. The orienteering problem: A survey. European Journal of Operational Research, 209(1), (2011) 1-10.
11. Vansteenwegen, P., Souffriau, W., Berghe, G. V., & Van Oudheusden, D. Metaheuristics for tourist trip planning. In Metaheuristics in the Service Industry. Springer Berlin Heidelberg. (2009) 15-31.
12. Wren A., Holiday A., Computer Scheduling of Vehicles from One or More Depots to a Number of Delivery Points. Operations Research Quarterly, vol. 23, (1972) 333-344.