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Conceptual paper

Dynamic Scoring and Costing in the Orienteering Problem: A Model Based on Length of Stay

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ABSTRACT

In today's travel and tourism landscape, the role of travel agents has become increasingly complex as they are challenged to explore a variety of potential destinations. More specifically, the complicated task of planning itineraries that truly satisfy travelers puts travel agents in a crucial role, increasing the complexity of itinerary planning. This complexity is compounded not only by the multitude of possible destinations, but also by non-negotiable constraints such as cost and time. To address these challenges, the orienteering problem represents a fundamental mathematical model that provides a theoretical basis for understanding the nuanced difficulties faced by travel agents. This study ventures into a novel iteration of the orienteering problem, with a particular focus on optimizing travel satisfaction based on length of stay. A notable aspect of this variant is the inclusion of time and cost constraints in the route determination process. Using an integer programming model, the satisfaction scores for each location are described by a diminishing returns function linked to length of stay, while the costs associated with each location follow a linear function influenced by the same parameter. The application of this model is in a hypothetical scenario with 32 nodes, with the calculations facilitated by the FilMINT solver. A sensitivity analysis examines time and cost constraints and shows their decisive influence on the optimization of travel routes. The results of this research contribute significantly to a strategic framework and provide travel agencies with the opportunity to create itineraries that not only meet practical limits but, more importantly, increase traveler satisfaction.

Keywords: orienteering problem, itinerary planning, travel satisfaction, integer programming, diminishing return function

INTRODUCTION

Tourism stands as a cornerstone of global economic prosperity, fostering cultural exchange and contributing significantly to national GDPs [1]. Within this vibrant industry, travel agents are indispensable, curating bespoke itineraries that ensure an optimal blend of cost-efficiency and enriching experiences. Their expertise in aligning logistical considerations with the nuanced preferences of travelers is crucial for sustaining the industry's growth, and the caliber of their service directly shapes the satisfaction and subsequent choices of tourists. Despite the pivotal role of travel agents in sculpting tourism experiences, there is a notable deficiency in routing models that intricately mesh the elements of customer satisfaction with the temporal evolution of associated costs. This research identifies and seeks to fill this void by proposing a novel orienteering problem model that intricately considers the diminishing returns of satisfaction in relation to time spent at each location, and the escalating costs that accompany it. Such a model promises to equip travel agents with a more sophisticated tool for itinerary planning, one that aligns with the complex, value-driven decisions faced by travelers today.

In an industry where myriad travel agents vie for consumer attention, the ability to differentiate through superior service quality becomes paramount [2]. Customer loyalty emerges as the currency of success, with tourists gravitating towards agents who consistently deliver beyond expectations. The intricacy of planning tours, amid a plethora of attractions and inherent time limitations, demands innovative solutions. Travel agents must navigate this competitive landscape with meticulous attention to detail, ensuring that each curated tour not only meets the logistical demands but also captures the essence of an unforgettable travel experience.

Travel agents face a complex task akin to the Orienteering Problem (OP), a mathematical formulation that encapsulates the essence of strategic route planning under constraints [3]. In OP, the objective is to select a sequence of destinations—nodes in the problem—that maximizes the traveler's experience within the confines of time and other resources [4]. This challenge mirrors the sport of orienteering, where individuals navigate to numerous checkpoints in an efficient sequence under time constraints [5]. The application of OP to travel planning allows agents to optimize itineraries, enhancing tourist satisfaction by systematically maximizing the value of each visit within the available time.

Our proposed OP model represents a significant advancement in the field by integrating time-dependent satisfaction and cost variables. This approach captures the dynamic nature of travel experiences, where the value derived from each destination is not static but evolves with the duration of the visit. By embedding these temporal factors into the OP framework, the model mirrors the fluid pricing strategies utilized in the tourism industry, providing travel agents with a more realistic and flexible tool for itinerary planning that is attuned to the modern traveler's expectations and the competitive nuances of the market. The application of orienteering problems in various conditions extends to scenarios such as travel salespeople with insufficient time to visit the entire city [6], home fuel delivery problems [7], single-ring design problems when building telecommunications networks [8], Mobile Tourist Guide [9], and planning to determine tourist destinations known as the Tourist Trip Design Problem (TTDP) [10]. In this study, where we apply orienteering problems to real conditions, the control point can be analogized as a tourist destination or city that can be visited. In the orienteering problem, not all control points need to be visited. This versatility showcases the adaptability of the orienteering problem across diverse scenarios, underscoring its relevance and effectiveness in addressing a wide range of real-world challenges beyond the scope of traditional travel-related applications.

In crafting travel itineraries, travel agents must consider a myriad of factors beyond time, including team dynamics [11], the timing of activities [12], specific time windows [13], diverse objectives [14], geographical clustering [15], variable time estimates [16], stochastic returns [17], and financial constraints [18]. The sophistication of the Orienteering Problem (OP) model becomes apparent as it encapsulates these real-life complexities, balancing the cost implications of longer stays [19] against the unique value proposition of each destination. These dynamics mandate a nuanced approach to maximize visitor satisfaction within the practical bounds of time and budget.

The intricacies of the Orienteering Problem (OP) are vividly illustrated through the scenario of visiting a theme park. Brief visits may be cost-effective, but they can result in a lower satisfaction score due to the limited number of attractions experienced. On the other hand, an extended stay can lead to greater enjoyment as visitors engage with more attractions, though at the expense of increased costs for additional amenities like food and drinks. The optimal visit length, therefore, becomes a delicate balance between experiencing a comprehensive range of attractions and managing physical fatigue and budgetary constraints, a principle that directly translates to the strategic decision-making in travel route optimization. Recognizing the variability in satisfaction scores and cost dynamics under different site conditions, it becomes imperative for a surgical model to account for diverse factors. These include time and cost limitations, and the scores that are influenced by the length of stay at each location. Building on the identified problem parameters, this research attempts to develop an orienteering problem model, of which satisfaction scores and cost depending on length of stay.

To date, the intersection of budgetary constraints, time-dependent satisfaction scores, and the principle of diminishing returns has not been fully explored within a unified mathematical model of orienteering problem. Current research primarily focuses on multi-profit and bi-objective orienteering problems, each incorporating elements of budget considerations and declining returns, yet a holistic model encompassing all these aspects remains absent from the literature. The Multi Profit Orienteering Problem (MPOP) reflects the dynamic needs of the tourism industry, where value is not static but varies with the timing of a visit [20]. In this model, the temporal aspect is crucial—profits from each tourist location fluctuate throughout the day, demanding that travel agents craft itineraries that tap into peak profit windows. The inherent variability in each location's appeal at different times necessitates a

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strategic approach to scheduling, making MPOP's principles central to the proposed OP model that seeks to optimize both traveler satisfaction and business profitability. MPOP can be represented on the graph G = (V, E) where V is a set of vertices $n + 2$ vertices and E is a set of arcs. The travel time t_{ij} is associated with the arc from vertex *i* to vertex *j* in *E*. In the set $V = \{v_o, v_1, \dots, v_n, v_{n+1}\}$, the first vertex v_o is the starting point, and the last vertex v_{n+1} is the end point . In many applications, v_o and v_{n+1} have the same position ($v_o \equiv v_{n+1}$) which is called a depot, whereas they differ in other applications. In the MPOP benchmark set, the start and end nodes are assumed to be different. In MPOP, each vertex *i* has as many time slots as Q_i, which can be represented as $\{[L_{i1}, L_{i2}], [L_{i2}, L_{i3}], \dots, [L_{iQ_i}, L_{iQ_{I+1}}]\}$. P_{iq} is the gain of vertex *i* associated with the time slot q^{th}. If the vehicle visits vertex *i* in the q^{th} time slot, it can accumulate the P_{iq} gain. The travel time limit is T_{max} to be able to complete the route.

The Bi-objective Orienteering Problem with Budget Constraint (BOOPBC) addresses a critical facet of travel planning—financial limitations [18]. By factoring in the tourist's budget, the BOOPBC model aligns with the real-world scenario where travelers must optimize their experience against cost constraints. This model delineates Points of Interest (POIs) by satisfaction categories, assigning varying scores based on cultural, entertainment, and other values. The aim is to curate an itinerary that maximizes the overall satisfaction score while adhering to both temporal and budgetary limits, reflecting the nuanced decision-making process travel agents navigate in actual practice. BOOPBC can be defined on the graph $G = (V, A)$ with a set of nodes = {0, 1, 2, ... , n +1} where 0 and n+1 are the must-visit start and end points, and one arc set $A = \{(i, j): i, j \in V, i \neq j, I \neq n+1, j \neq 0\}$. In each arc $(i, j) \in A$ there is a cost value C_{ij} which can represent the time or distance it takes to travel from vertex *i* to vertex *j*. Each vertex $i \in V \setminus \{0, n+1\}$ has two advantages or Point of Interest (POI), namely p_{1i} and p_{2i}. Each vertex $i \in V$ has bi costs that need to be incurred when visited. The purpose of BOOPBC is to determine a route that is limited by a maximum time limit of T and is limited by a maximum budget limit of B, so that the total profit collected corresponds to the amount of each profit from each vertex contained in the route formed. Building on the foundation of the BOOPBC, this study hypothesizes that incorporating budget constraints and time-dependent satisfaction into the OP model will result in a more detailed and accurate representation of the complex decision-making process involved in travel planning. The research questions posed aim to determine the extent to which this refined model can predict actual traveler decisions and the effectiveness with which it can improve the service quality of travel agencies in the competitive tourism landscape.

The concept of diminishing returns, as expounded by economic theorists like von Thunen and Ricardo, is pivotal to understanding the interplay between satisfaction and cost within tourism [21][22]. It posits that beyond a certain threshold, the incremental benefit gained from an additional unit of consumption decreases. Applied to tourism, this principle suggests that the enjoyment derived from extended stays at a destination may eventually plateau or even decline, whereas costs continue to accrue. This nuanced economic insight necessitates a refined OP model that can adeptly balance the diminishing satisfaction against the incremental costs, thus optimizing the tourist's itinerary. The principle of diminishing returns extends beyond its traditional economic roots to encapsulate facets of human behavior and the pursuit of satisfaction [23]. This principle, often referred to as the law of diminishing marginal utility, posits that beyond a certain consumption threshold, each additional increment yields progressively less pleasure or satisfaction [24]. This diminishing utility is particularly relevant to the tourism sector, where the experiential quality of a destination may wane with time spent, guiding the need for an OP model that balances the desire for extensive exploration against the propensity for over-saturation.

The Law of Diminishing Marginal Returns states that the quantity of an input added exceeds a certain limit can be dangerous for consumers because it does not lead to pleasure, even happiness [23]. According to [25] time is a resource that can provide an increased value associated with better opportunities for use and decreased value associated with resource abundance, so time can be used as input for diminishing returns. Experiencing new experiences at an early stage can produce high utility, but over time it will experience diminishing marginal utility. Based on this, the satisfaction score obtained from the visited locations follows the diminishing return concept where the satisfaction score at the location becomes the output and the length of time staying at the location becomes the input. The mathematical equation for the satisfaction score, which is influenced by one factor, namely residence time can be described as follows:

$$S(h_i) = -a_i h_i^3 + b_i h_i^2 + c_i h_i \tag{1}$$

The calculation of the satisfaction score or $S(h_i)$ in Equation (1) depends on the duration of the visit to location i (h_i). The constants a_i, b_i, and c_i are unique to each location and are based on their individual characteristics. For example, a theme park would provide a satisfaction score that initially increases and then decreases as the visitor gets tired. Similarly, a restaurant would provide a high satisfaction score initially, but it would decrease if the waiting time were too long.

The remainder of this paper is structured to systematically unfold the research conducted. The forthcoming section delineates the methodology employed to refine the OP model, integrating time and cost considerations. Subsequently, a case study is presented to illustrate the model's practical application, followed by an analysis of the results. The discussion then pivots to the broader implications of these findings within the tourism industry. Finally, the paper concludes with reflections on the potential impact of this research on travel planning practices and recommendations for future investigations in this domain.

METHODS

Previous studies on orienteering problems have been reviewed in this section, and their findings are presented. The research synthesis results provide an overview of the research in comparison to earlier studies. We conducted research synthesis by reviewing literature from various sources such as international journals, articles, and books.

Various variations of the Orienteering problem that have been studied so far are such as (Team) Orienteering problem [5], Orienteering problem with Time Windows [13], Team Orienteering problem with Time Windows [26], Multi objective (Team) Orienteering problem with Time Windows [27], Bi-Objective Orienteering problem [28], Time-Dependent Orienteering problem with Time Windows [29], Set Orienteering problem [30], Capacitated Team Orienteering problem [31], Time-Dependent Orienteering problem [12], Multi-objective Time-Dependent Orienteering problem [32], Generalized Orienteering problem with Resource Dependent Rewards [33], Orienteering problem with Service Time Dependent Profit [34], Orienteering problem with Stochastic Travel and Service Time [16], Orienteering problem with Variable Profit [19], Orienteering problem Stochastic Profits [35], Multi-Profit Orienteering problem [20], Bi-Objective Orienteering problem with Budget Constraint [18], and others. Relation between this research and previous research are shown in Figure 1.

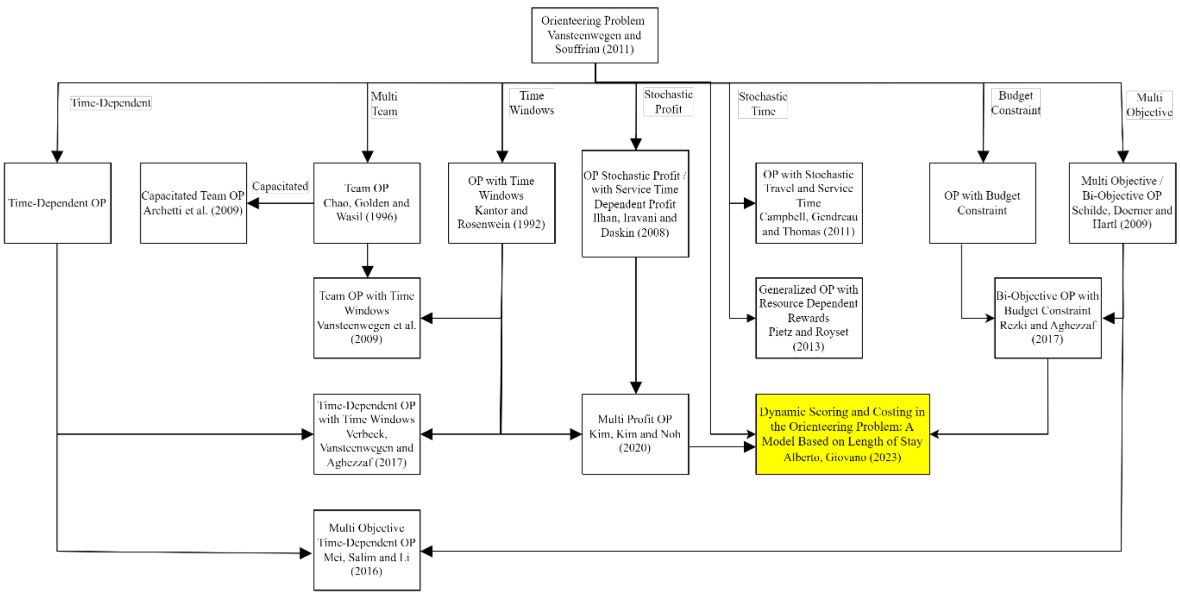

Figure 1. Relation with Previous Literature

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Development of an Orienteering Problem (OP) model involves considering the satisfaction levels of each Point of Interest (POI) based on categories or multiple objectives. Multi-objectives arise because each visitor has unique interests, such as culinary and culture. Each category presents numerous options, like cafes or restaurants [28]. Several researchers have developed an optimization problem (OP) that considers multiple objectives by combining time-dependent, multi-team, and time windows. For example, visitors who are interested in nature would prefer a restaurant with natural vibes in a forest, while those who enjoy luxury design would prefer a restaurant with a luxurious ambiance.

Moreover, the OP model considers travel time to a location that is not fixed and depends on resources such as fuel or time. This can be modelled using Orienteering problems with Stochastic Travel and Service Time [16]. Additionally, a location's score may vary based on factors such as the duration of stay or energy expended. Such models have been explored in studies like the Generalized Orienteering problems with Resource Dependent Rewards [33] and Orienteering problems with Stochastic Profits [35]. There is also research that considers satisfaction score at a location based on the arrival at a certain time window, as in the Multi-Profit Orienteering problem [20].

Building on the foundation of the mathematical model proposed in [18] and [20], which incorporates the concept of diminishing returns, the development orientation problem in this study delves into a more practical area by taking into account budget constraints and closely adapting them to real-world conditions. While [18] takes budget constraints into account and thus makes them applicable, the variation in satisfaction scores based on arrival time presented in [20] is also taken into account. In contrast, this study uniquely examines the influence of time spent in each location on satisfaction scores of which increasing the time spent at a single location increases overall satisfaction scores. However, at a certain point, this score ultimately decreases due to factors such as fatigue and boredom. Besides, the complicated task of solving the orienteering problem requires decisions about which locations to visit, in what order, and how long to stay at each location, based on satisfaction scores and costs which are dynamically affected by length of stay. Furthermore, the proposed model introduces two critical constraints - time and cost - that must be carefully managed to ensure optimization. The developed OP model is based on the classic OP model [3] and includes basic concepts of objective function, constraints and sub-tours elimination, thus forming a robust framework for strategic decision making in route planning.

In the developed orienteering problem model, the set of locations that can be visited is represented by n. Orienteering problems with respect to satisfaction scores and costs depending on the length of stay can be defined as a graph $G = (V, A)$ where V is a collection of locations that can be visited in total of $n+2$ and A is the entire path connecting one location to another. In the set $V = \{0, 1, \ldots, n, n+1\}$, 0 is the starting point and $n+1$ is the end point of the resulting route. Afterward, set $A = \{(i, j): i, j \in V, i \neq j, i \neq n+1, j \neq 0\}$. Each arc $\{(i, j) \in A$ has a cost value t_{ij} which represents the time required to travel from vertex i to vertex j.

Each vertex $i \in V \setminus \{0, n+1\}$ has a cost that follows a linear function and a satisfaction value that follows a diminishing returns function, with length of stay having an impact on both values. The developed OP model aims to maximize the overall satisfaction rating by determining the best route and length of stay at each location while adhering to specific total time and total cost constraints. The following mathematical formualtions are used in the proposed OP problem:

Notations:

a_i, b_i, c_i	The constant of the diminishing return function depends on the length of stay at location i
n	Number of control points or locations that can be visited
y_i	Value 1 if visiting location i (other 0).
x_{ij}	Value 1 if visiting location i followed by visiting location j (other 0).
t_{ij}	Travel time from location i to j
h	Length of stay at location i
T	Maximum timeout of generated route

$b(h_i)$	A linear cost function which depends on the length of stay at the location i
d_i, e_i	A constant in a linear cost function with a length of stay at location i
B	Maximum cost limit of generated route routes
u_i	Used within sub tour elimination constraints and allows to determine the position of the visited node on the path

Objective function:

$$Max \sum_{i=0}^{n} \sum_{j=1}^{n} \left(-a_j h_j^3 + b_j h_j^2 + c_j h_j\right) x_{ij} \tag{2}$$

s.t.:

$$\sum_{j=1}^{n+1} x_{0j} = \sum_{i=0}^{n} x_{i,n+1} = 1 \tag{3}$$

$$\sum_{i=0}^{n} x_{ik} = \sum_{j=1}^{n+1} x_{kj} \leq 1, \ \forall\, k = 1, \cdots, n \tag{4}$$

$$\sum_{i=0}^{n} x_{ik} = \sum_{j=1}^{n+1} x_{kj}, \ \forall\, k = 1, \cdots, n \tag{5}$$

$$\sum_{i=0}^{n} \sum_{j=1}^{n+1} t_{ij} x_{ij} + h_j x_{ij} \leq T \tag{6}$$

$$\sum_{i=0}^{n} \sum_{j=1}^{n+1} \left(d_j h_j + e_j\right) x_{ij} \leq B \tag{7}$$

$$u_0 = 1 \tag{8}$$

$$2 \leq u_i \leq n, \ \forall\, i = 1, \ldots, n \tag{9}$$

$$u_i - u_j + 1 \leq (n+1)\left(1 - x_{ij}\right), \ \forall\, i, j = 1, \ldots, n \tag{10}$$

$$x_{ij} \in \{0,1\}, \ \forall\, i, j = 1, \ldots, n \tag{11}$$

$$h_i \geq 1, \ \forall\, i = 1, \ldots, n \tag{12}$$

$$a_i, b_i, c_i, d_i, e_i > 0, \ \forall\, i = 1, \ldots, n \tag{13}$$

$$a_i < b_i \text{ and } a_i < c_i, \ \forall\, i = 1, \ldots, n \tag{14}$$

Equation (2) is the objective function of the developed model, to maximize the score collected from customers. S(hi) is a diminishing return function for location i where the score is obtained depending on the length of time used at location i. Furthermore, equation (3) ensures that the vehicle starts and ends at a predetermined location. Equation (4) to ensure that each location is visited at most once. Equation (5) ensures that if a location is visited, it will be worth 1 for both values and the other is 0. Equation (6) is to ensure the total travel time taken and time to visit a location does not exceed the maximum time limit T. Then equation (7) limits the total cost in the visited locations on the route not to exceed the maximum cost limit. B. The total cost used at one location follows a linear function which is influenced by the length of stay. Equations (8), (9), and (10) to ensure that no sub tour occurs. Equation (11) is a binary value decision variable. In Equations (12) and (13) ensure that the visit time is greater than 1 and the constant for the score and cost function is greater than 0. Whereas in Equation (14) the value of ai must be less than the value of bi and ci to produce a curve that is desired. Based on this mathematical model, the problem formed is a non-linear mix integer programming originating from objectives, constraints, and decision variables.

RESULTS AND DISCUSSION

In order to verify and apply mathematical models, hypothetical cases are created to study orienteering problems that depend on length of stay, which have not been previously researched. In this hypothetical case, we require a few data points such as location coordinates, satisfaction constants, and cost constants. This case consists of 32 nodes with 2 nodes as the start and end locations. This case is solved using FilMINT. The coordinate data of each location are in Appendix A.1 and constant for satisfaction scores and costs at each location are in Appendix A.2. The location of each node is visualized in Figure 2.

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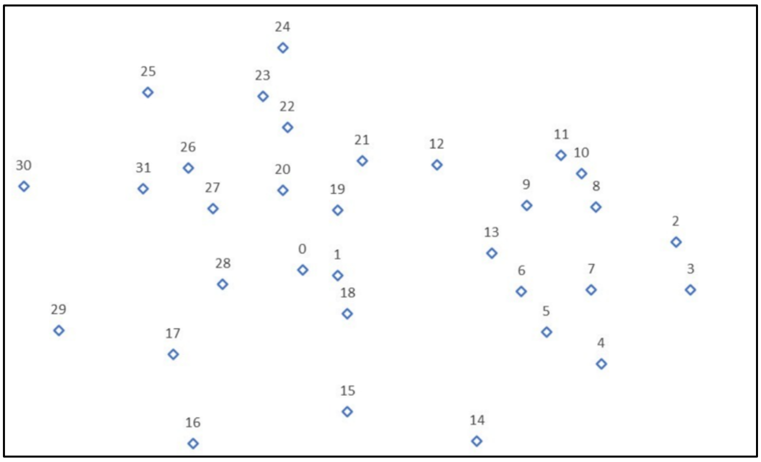

Figure 2. Location of Nodes

An AMPL model was created to code the orienteering problem, considering scores and costs that vary over time. The following summarizes the results of the case implementation of the time-dependent orienteering model, with constraints on time and cost. The maximum time limit was set to 8, and the maximum cost was limited to 35:

1. The total satisfaction score obtained is 203.76 with the total time used is 8 and the total cost used is 8.69;
2. The route formed is to visit 3 of the 30 available locations;
3. The order of locations visited on the route formed is the initial location as: location 0 → location 20 → location 11 → location 21 → location 31 (final location);
4. The visiting time of each location 20, 11 and 2 are 2.07 hours, 1 hours and 1 hours, respectively.

The findings demonstrate that while the overall time taken is 8, which is equal to the maximum time permitted, the total budget expense is 8.69, which is significantly less than the maximum budget. The sum of the travel time and the amount of time spent visiting each location is used to determine the overall time. The outcomes comply with every restriction that was mentioned in the model's formulation.

After verifying that the model solves a case, a sensitivity analysis is conducted for different parameters. The objective of this sensitivity study is to determine the degree of sensitivity of the total score to changes in parameter values. To conduct the sensitivity analysis, the study used the maximum time limit, maximum budget limit, and a combination of these two parameters. The study considered the percentage of parameter change at -60%, -40%, -20%, 20%, 40%, and 60% to demonstrate the fluctuating values in real-world scenarios. The results are presented in Appendix A.3 and visualized in Figure 3.

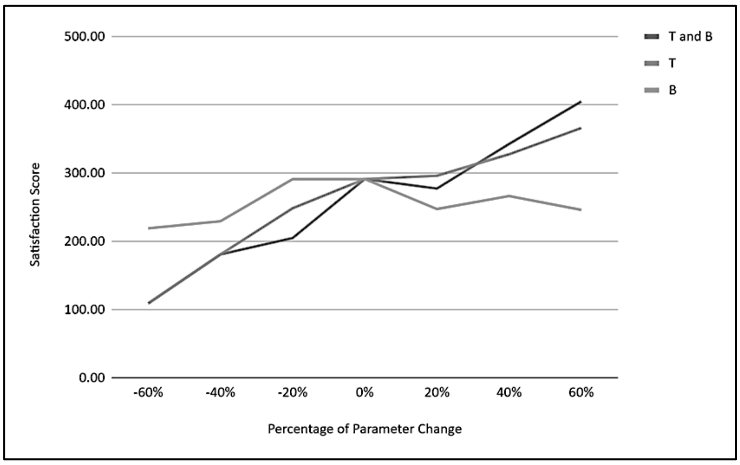

Figure 3. Chart of Sensitivity Analysis

The analysis clearly shows that maximizing the total time has the greatest impact on the satisfaction score. It is evident that reducing the time constraint affects the score more than reducing the budget constraint. The highest score increase is achieved by increasing both parameters. Therefore, to achieve higher satisfaction, it is imperative to increase the maximum time limit.

CONCLUSION

This research describes the successful formulation of an orienteering (OP) problem model that accounts for the nuanced relationship between length of stay and its resulting impact on satisfaction and cost – a reflection of the complex travel planning dynamics in the real world. The central challenge of the model is the strategic selection and sequencing of travel destinations in order to optimize the satisfaction score within given time and cost constraints. Our results suggest that time constraints significantly influence satisfaction scores, with significant declines observed with stricter time constraints. Conversely, a synergistic increase in time and budget allocations can significantly increase satisfaction scores and illustrates the delicate balance that travel agencies must manage. This study's implications extend beyond theoretical constructs, suggesting a pragmatic approach for travel agents in crafting itineraries that maximize traveler satisfaction. The sensitivity analysis underscores the model's robustness and its potential as a decision-making tool in the tourism industry, where the allocation of time is as critical as the management of costs.

To further improve the applicability of the OP model, it is advised that the model be thoroughly validated through real-world application in order to verify the satisfaction scores, travel time, and related expenses. To improve the model's performance and account for complicated scenarios like fluctuating fuel prices, more research may involve applying different heuristic or metaheuristic algorithms. To further enhance its applicability to a wider range of travel planning scenarios, the model can be extended to include team orienteering dynamics or particular time windows. Overall, this work represents a major advancement in the field of travel route optimization, offering a strong basis for further empirical research and the creation of advanced instruments for the travel and tourism sector.

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CONFLICT OF INTEREST

This work is free from any conflicting associations, monetary involvements, or personal affiliations that might raise questions about the objectivity or impartiality of the reported research.

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Appendix

A.1. Coordinate Data of Hypothetical Location

Location	Coordinate *x*	Coordinate *y*	Location	Coordinate *x*	Coordinate *y*
1	1.55	1.78	17	0.95	0.03
2	1.73	1.72	18	0.84	0.92
3	3.58	2.06	19	1.79	1.33
4	3.66	1.57	20	1.73	2.37
5	3.17	0.83	21	1.44	2.58
6	2.87	1.15	22	1.87	2.87
7	2.74	1.55	23	1.46	3.21
8	3.12	1.57	24	1.33	3.52
9	3.14	2.41	25	1.44	4.01
10	2.76	2.43	26	0.71	3.56
11	3.06	2.74	27	0.92	2.80
12	2.95	2.93	28	1.06	2.39
13	2.28	2.84	29	1.11	1.63
14	2.57	1.94	30	0.22	1.16
15	2.49	0.05	31	0.03	2.61
16	1.79	0.35	32	0.68	2.59

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A.2. The constant of the diminishing return function

The diminishing return function								**The linear cost function**					
Node	a_i	b_i	c_i	**Node**	a_i	b_i	c_i	**Node**	d_i	e_i	**Node**	d_i	e_i
0	0	0	0	16	9	20	19	0	0	0	16	1.76	2
1	8	20	16	17	8	26	23	1	1.18	2	17	1.61	5
2	5	15	26	18	4	23	29	2	0.43	4	18	0.76	5
3	4	17	16	19	9	21	24	3	1.87	5	19	0.11	5
4	6	28	16	20	4	15	23	4	0.77	3	20	0.54	1
5	9	20	19	21	9	28	25	5	0.97	4	21	0.38	3
6	3	19	19	22	8	17	22	6	1.63	4	22	1.89	2
7	7	28	15	23	9	25	22	7	0.98	3	23	1.74	3
8	10	29	25	10	5	21	24	8	1.19	2	24	1.60	1
9	6	25	27	6	9	28	25	9	0.79	2	25	1.02	5
10	6	17	20	6	8	27	19	10	1.03	5	26	1.67	3
11	3	23	26	3	6	26	23	11	1.34	1	27	1.32	4
12	4	16	18	4	9	21	27	12	1.21	2	28	1.33	4
13	4	27	18	4	4	18	15	13	0.76	2	29	1.41	4
14	8	27	27	8	7	23	15	14	1.69	4	30	0.81	2
15	7	19	19	7	0	0	0	15	0.17	4	31	0	0

A.3. The result of sensitivity analysis

T	B	a_i	b_i	c_i	d_i	e_i	**Scores**	**Changes**	**Route**
10	35	1	1	1	1	1	291.16	0%	0 - 18 - 1 - 19 - 20 - 27 - 26 - 31
4	14	1	1	1	1	1	108.93	-63%	0 - 27 - 26 - 31
6	21	1	1	1	1	1	180.64	-38%	0 - 28 - 27 - 26 - 31
8	28	1	1	1	1	1	204.70	-30%	0 - 18 - 1 - 19 - 20 - 27 - 31
12	42	1	1	1	1	1	277.27	-5%	0 - 9 - 13 - 8 - 10 - 12 - 21 - 31
14	49	1	1	1	1	1	342.70	18%	0 - 18 - 7 - 8 - 9 - 12 - 21 - 19 - 27 - 31
16	56	1	1	1	1	1	404.79	39%	0 - 19 - 9 - 8 - 10 - 11 - 12 - 21 - 22 - 23 - 26 - 31
4	35	1	1	1	1	1	108.93	-63%	0 - 27 - 26 - 31
6	35	1	1	1	1	1	180.64	-38%	0 - 28 - 27 - 26 - 31
8	35	1	1	1	1	1	248.41	-15%	0 - 18 - 19 - 20 - 27 - 31
12	35	1	1	1	1	1	296.05	2%	0 - 18 - 28 - 27 - 19 - 21 - 22 - 26 - 31
14	35	1	1	1	1	1	327.46	12%	0 - 1 - 18 - 6 - 4 - 5 - 7 - 13 - 31
16	35	1	1	1	1	1	365.92	26%	0 - 18 - 8 - 9 - 10 - 21 - 24 - 23 - 25 - 31
10	14	1	1	1	1	1	218.94	-25%	0 - 20 - 21 - 8 - 9 - 31
10	21	1	1	1	1	1	229.34	-21%	0 - 8 - 9 - 20 - 27 - 26 - 31
10	28	1	1	1	1	1	291.16	0%	0 - 18 - 1 - 19 - 20 - 27 - 26 - 31
10	42	1	1	1	1	1	247.27	-15%	0 - 13 - 8 - 9 - 21 - 27 - 31
10	49	1	1	1	1	1	266.36	-9%	0 - 19 - 1 - 18 - 20 - 26 - 31
10	56	1	1	1	1	1	246.00	-16%	0 - 8 - 9 - 13 - 21 - 31

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