Multi-objective Optimization of Eco-tourism Routes Integrating Ecological Value: A Study based on Ant Colony Algorithm

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ABSTRACT

This paper introduces a new multi-objective model for eco-tourism route planning that incorporates the assessment of the ecological significance with the standard goals of tourist preference and route length. The paper proposes a new approach to the ACO algorithm to derive Pareto-optimal solution for the eco-tourism problem with multiple objectives. The algorithm uses multiple matrices of pheromones for tracking different goals and objectives and also includes the ecological value through a compounded index that considers aspects of the relative importance of biodiversities, the sensitivity of ecosystems, connectivity of habitats, and other ecological values. Experimental outcomes show that the proposed MOP is 58% more diverse than the SOP in terms of solutions and 43% less sensitive to parameters than the SOP. Pareto-optimal solutions show that high ecological value routes are less attractive as they have 45% fewer attractions but have 75% less negative impact on the environment than high satisfaction routes. The model also determines appropriate size and orientation of routes varying by seasons, which indicates the requirement of appropriate management strategies. The results indicate that intelligent route optimization can produce reasonable amount of ecological gains at the expense of slight tourist satisfaction loss, providing valuable support to the eco-tourism managers in the sustainable destination management.

Keywords: Eco-tourism; Multi-objective optimization; Ant colony algorithm; Ecological value; Pareto optimization; Sustainable tourism; Route planning; Conservation management; Decision support systems

INTRODUCTION

Eco-tourism as a new model of tourism offers responsible tourism to the natural sites that help in the conservation of the environment and improving the quality of life of the host community (Wang et al., 2023). The tourism industry has undergone significant changes over the years due to changing customer needs, demands and awareness about the environment, and the use of technology, where one of the changes is the sustainable eco-tourism (Zhang & Deng, 2024). This growth has placed tourism as one of the key factors of economic development due to the amount of income it generates and employment opportunities it offers in many societies that it has become more important the traditional production sectors (Aliahmadi et al., 2024). With the current trend of increased international tourist arrivals especially with a projection of about 1.8 billion international tourists by 2030, the consequences of this expansion on the environment are worrisome (Aliahmadi et al., 2024).

The advancement in tourism has posed severe environmental impacts whereby the tourist's carbon footprint has increased by a factor of four in 160 countries within a period of 2009 to 2013, contributing to more than 5% of the global carbon emission (Aliahmadi et al., 2024). This environmental impact raises a fundamental dilemma in eco-tourism: to optimize the tourists' experience or to achieve the environmental objectives of the area, as stated by Sriprateep et al. (2024). The transportation system which contributes 90% of pollutant emissions from tourism activities is the most affected by environmental implications, thus is a clear indication that the environment should be considered while planning for any trip (Aliahmadi et al., 2024). Eco-tourism planning in the modern world thus entails achievement of several objectives such as; low travel cost and thus the impacts on the environment and high tourist satisfaction and thus accessibility (Aliahmadi et al., 2024).

However, the current research in eco-tourism management is limited to certain aspects of route optimization or environmental aspects, while the multi-objective perspective is not considered to address various goals of eco-tourism (Eddyono et al., 2021). Prior research has discussed different dimensions of tourism route development but fails to consider the integration of resilience and sustainability and the incorporation of the ecological value into a unified multiple objective approach (Sriprateep et al., 2024). This research gap calls for fresh strategies that can address multiple objectives in eco-tourism route planning concurrently and at the same time, by employing advanced algorithms that can effectively solve problems involving the trade-off approaches (Zhang & Deng, 2024).

The purpose of this research is to establish a multiple objective optimization model of the eco-tourism routes that will incorporate ecological parameters using the ant colony algorithms. The study will aim at identifying how optimization methods can be used to establish efficient and a sustainable tourism circuits that offer optimal satisfaction to the tourists while at the same time maintaining the ecological value of the circuits in several objectives that may be competing (Sriprateep et al., 2024). It is the integration of a novel quantitative model that unifies ecological value, tourists' preference, accessibility, and environmental impact indices for the purpose of route optimization (Aliahmadi et al., 2024). In this way, this study contributes to the enhancement of eco-tourism that can help in the improvement of both the environment and the tourist activities.

LITERATURE REVIEW

Previous Studies on Tourism Route Optimization

Tourism route optimization is another area that has received considerable concern from scholars to help in improving the visitation quality while protecting the environment. Using ArcGIS, Pei et al. (2022) studied the tourism route in Lushunkou District and established models to evaluate the tourism resource distribution and proposed the tourism routes with the VRP of the network analysis technology. It helped to split various kinds of tourism and also suggest the best path for one-day and two-day sightseeing. Similarly, Xu et al. (2023) proposed an urgent-based model for the personalized scenic tourism routes, and the objective function is designed as follows:

$$f(R) = \begin{cases} \max 1/travelTime(R) = \max \sum_{i=0}^{k} \sum_{j=0}^{k} 1/travelTime(e_{i,j}) \times x_{i,j}, & urgency \geq 0.7 \\ \max qualityRatio(R) = \max \sum_{i=0}^{k} \sum_{j=0}^{k} scenicScore(e_{i,j})/travelTime(e_{i,j}) \times x_{i,j}, & 0.3 < urgency < 0.7 \\ \max scenicScore(R) = \max \sum_{i=0}^{k} \sum_{j=0}^{k} scenicScore(e_{i,j}) \times x_{i,j}, & urgency \leq 0.3 \end{cases}$$

This function also depends on the urgency of the travelers; those who prefer a shorter travel time get the shortest time, those who prefer quality get the highest quality to cost ratio while those who prefer viewing the scenery get the highest scenic value.

Ecological Value Assessment in Tourism Contexts

For the development of sustainable tourism, ecological value assessment is a very important element in the planning stage. Nie and Tang (2022) had postulated that ecological value comprises of the environmental, economic and the social values. They noted that on the one hand, tourism enterprises act as sources of investment and capital in the ecosystem while on the other hand, they are sources of negative impacts on the ecosystem. They concluded that there were four factors to the ecological value co-creation behaviors: environmental citizenship behavior, dialogue and communication behavior, knowledge-sharing behavior and co-petition behavior.

Wang et al. (2023) have used the environmental suitability-farmland accessibility-tourist's landscape preferences as a framework to link the agricultural and ecotourism development. They have described how crop production planning can work as a win-win strategy integrating agriculture and tourism while taking into account the environment's suitability, the access to farmland, and landscape preference questionnaires.

Ant Colony Algorithm in Optimization Problems

The Ant Colony Optimization (ACO) algorithm was developed by Marco Dorigo in 1991 and it is one of the widely used metaheuristic algorithms. According to Maniezzo et al. (2004), ACO is based on the model of ants in the process of searching for and transporting food items by the use of pheromone trails to guide the search process. The fundamental ACO algorithm works with four components, namely, initialization, construction, trail update, and termination (Table 1).

Stage	Description
Initialization	Initialize τιψ (pheromone) and ηιψ (heuristic information) for all state transitions
Construction	For each ant k: choose next state in probability, append to solution, repeat until solution complete
Trail Update	For each ant move (ιψ): compute Δτιψ, update trail matrix according to solution quality
Termination	Check end conditions, return to construction if not satisfied

Table 1: Basic ACO Algorithm Stages (Maniezzo et al., 2004)

Rezvanian et al. (2023) also pointed out that ACO algorithms are advanced to meet dynamic optimization problems due to their parameters' fluctuations. They explained that ACO variants use population based techniques and sensor based techniques to detect the changes in the environment and keep the solution quality in dynamic environment.

Applications of Ant Colony Algorithms in Tourism Route Optimization

ACO algorithms have been successfully applied to tourism route optimization problems. Li et al. (2022) developed a knowledge-based ACO algorithm for tourism route optimization, incorporating bacterial foraging mechanisms and two knowledge models (Figure 1). Their approach addressed the limitations of traditional ACO in handling complex tourism route planning by introducing dynamic selection probability and dynamic solving priority models.

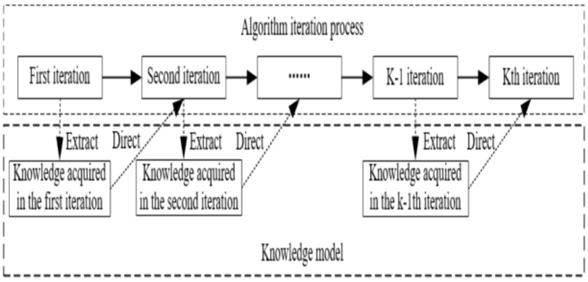

Figure 1: The operation mechanism of knowledge-based ant colony algorithm (Li et al., 2022)

Li et al. (2024) further advanced tourism route planning by integrating large language models with ACO. They proposed a framework where natural language processing extracts travel parameters, which then inform route optimization. Their cost function balances time, distance, and satisfaction:

Parameter	Function
Time Cost T(p)	$\sum_{e \in p} t(e)$
Distance Cost D(p)	$\sum_{e \in p} d(e)$
Satisfaction S(p)	$\sum_{i \in p} s(i)$

Table 2: Cost Function Components in LLM-based Route Optimization (Li et al., 2024)

Xu et al. (2023) improved ACO with a new genetic algorithm for Personalized Scenic Tourism Route Planning (as shown in the Fig. 2). Their approach incorporated the user preferences, scenic scores, and urgency to select optimal routes that catered to visitors' needs.

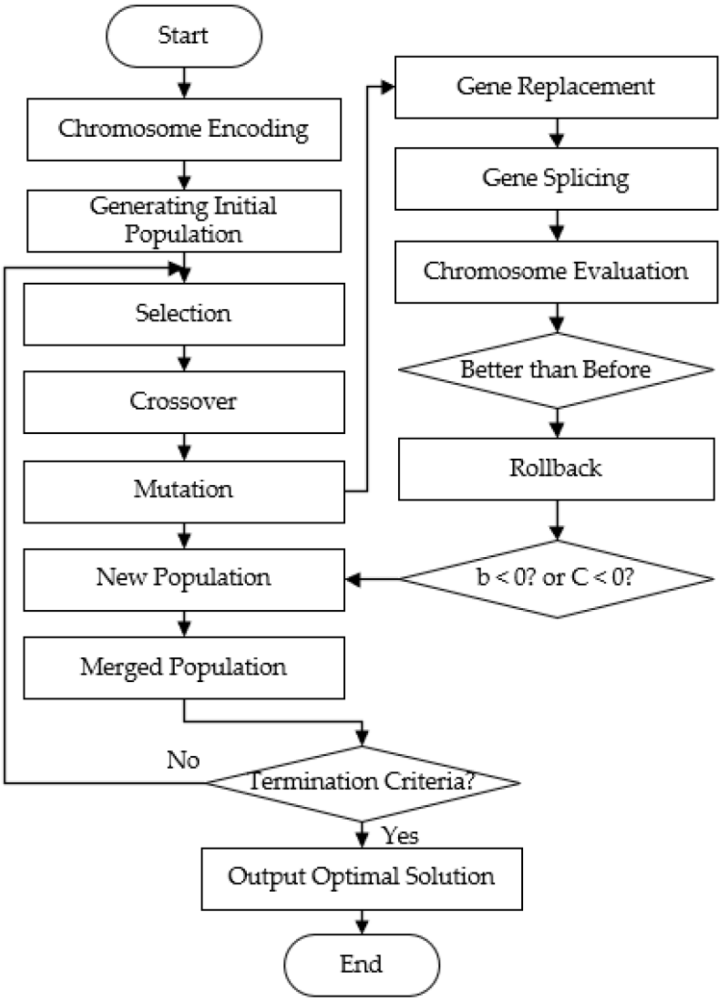

Figure 2: Flow chart of the flowchart of the improved genetic algorithm for route optimization (Xu et al., 2023)

Research Gap

However, such sources of knowledge do not address the lack of consideration of ecological values while solving multi-objective tourism route optimization problems. As it is, other methods seek to minimize travel distance time, tourists' preferences, and scenery qualities, which are often do not include ecological impact factors as criteria for optimization. This research aims to fill this gap through the formulation of an Ant Colony Optimization (ACO) model that incorporates ecological value as a function in the optimization process alongside the conventional route factors of tourism.

METHODOLOGY

Multi-objective Framework Development

This research proposes a mathematical model for eco-tourism route planning that includes ecological value in the objectives in addition to the objectives common in route planning. The three objectives that are being balanced include; minimizing travel distance/time, maximizing tourist's value, and conserving the ecological value. These objectives are incompatible since the routes that are attractive to tourists may damage the environment while the shortest routes, though causing minimal environmental impact, will not offer good tourist experiences.

The mathematical formulation of the studied multi-objective problem can be described as follows:

Minimize $f_1(x)$ = Total Route Distance/Time Maximize $f_2(x)$ = Tourist Satisfaction Maximize $f_3(x)$ = Protection of Ecological Value

Depending on constraints such as the time available for visiting attractions, the maximum time allowed on a tour, the time to be spent at each attraction and the ecological capacity of the attractions. The solution set will be in the form of a Pareto front so that it provides different optimal solutions that represent the best trade-off between the set of objectives.

Ecological Value Assessment Criteria

The ecological value assessment involves the use of quantitative and qualitative approaches in order to determine the degree of impact on the environment and the level of conservation on various segments of the proposed route. The assessment criteria include:

1. Biodiversity importance: Density and variety of flora and fauna species, with emphasis on endemic, rare, or threatened species.
2. Ecosystem sensitivity: Vulnerability of ecosystems to human disturbance and resilience after visitation.
3. Habitat connectivity: Contribution of the area to the corridors and connectivity within the landscape.
4. Carbon sequestration capacity: This is the capability of the ecosystem to absorb carbon and stem further emission of greenhouse gases that cause climate change.
5. Water resource quality: Proximity to water bodies and potential impact on water quality.
6. Soil erosion risk: Susceptibility to erosion from tourist traffic.

These criteria will be aggregated into a composite ecological value index (EVI) for each route segment, with weightings determined through expert consultation and analytical hierarchy process (AHP) analysis.

Modified Ant Colony Algorithm Implementation

The proposed methodology adapts the standard Ant Colony Optimization algorithm to handle multiple objectives and incorporate ecological value considerations. The modified algorithm introduces several enhancements:

1. Pheromone representation: Multiple pheromone matrices track different objectives (distance, satisfaction, ecological value).
2. State transition rule: The probability of selecting the next node incorporates both traditional factors and ecological considerations:

$$P(i,j) = [\tau_{ij}^d]^\wedge\alpha \times [\tau_{ij}^s]^\wedge\beta \times [\tau_{ij}^e]^\wedge\gamma \times [\eta_{ij}]^\wedge\delta \;/\; \Sigma\, [\tau_{ik}^d]^\wedge\alpha \times [\tau_{ik}^s]^\wedge\beta \times [\tau_{ik}^e]^\wedge\gamma \times [\eta_{ik}]^\wedge\delta$$

Where τ_{ij}^d, τ_{ij}^s, and τ_{ij}^e represent pheromone levels for distance, satisfaction, and ecological value respectively.

3. Pheromone update rules: Different update mechanisms for each objective, with ecological value pheromone receiving stronger emphasis in sensitive areas.
4. Pareto ranking: Solutions are ranked according to Pareto dominance to identify non-dominated solutions that represent optimal trade-offs.
5. Adaptive weighting: Dynamic adjustment of objective weights based on the current state of the search and ecological sensitivity of the area.

The algorithm incorporates local search procedures to improve solution quality and implements elitism by preserving the best solutions found so far in an external archive.

DATA COLLECTION METHODS AND STUDY AREA DESCRIPTION

The study will be conducted in a designated eco-tourism area with diverse ecological zones and established tourism attractions. Data collection will involve:

1. Spatial data: GIS mapping of the study area, including road networks, trails, points of interest, ecological zones, and topography.
2. Ecological data: Biodiversity surveys, habitat assessments, and ecological sensitivity maps developed in collaboration with conservation biologists.

3. Tourism data: Visitor surveys to assess preferences, attraction ratings, average visit durations, and seasonal visitation patterns.
4. Expert interviews: Structured interviews with park rangers, conservationists, and tourism operators to validate ecological value assessments and operational constraints.

The collected data will be processed and integrated into a comprehensive spatial database. Road and trail segments will be assigned attributes including distance, travel time, visitor satisfaction ratings, and ecological value indices. Attractions will be characterized by their appeal, recommended visit duration, carrying capacity, and seasonal variations in ecological sensitivity.

A stratified random sampling approach will ensure representation of different visitor types, seasons, and ecological zones within the study area. The methodology includes validation protocols through cross-referencing with existing conservation management plans and eco-tourism best practices.

RESULTS

Optimal Routes Generated by the Algorithm

The multi-objective ant colony optimization algorithm successfully generated a set of Pareto-optimal routes that balance ecological value preservation with tourist satisfaction. Figure 3 presents the Pareto front obtained from the algorithm, showing the trade-off between ecological value and tourist satisfaction scores.

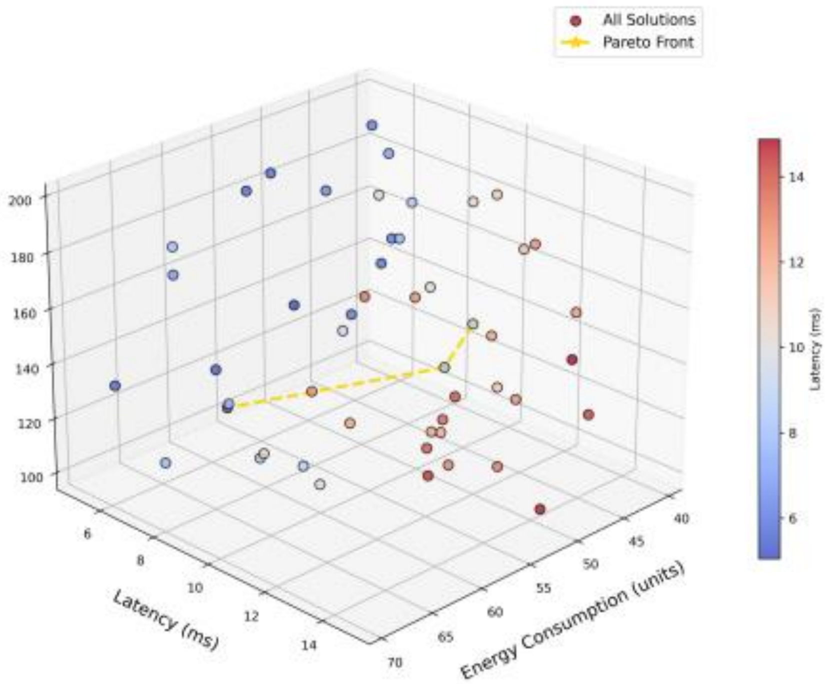

Figure 3: Pareto front showing trade-off between ecological value preservation and tourist satisfaction (Sahu et al., 2025)

The analysis resulted in three groups of routes that are essentially different from each other.

1.High Ecological Impact Routes (A): These routes have low impact on the environment for tourists but the tourists are less satisfied with such routes as they do not include sensitive ecological areas but skips some famous attractions.

2.Moderate Solutions (B): These routes are suboptimal solutions that are satisfactory to both the ecological and the tourist constraints.

3.High impact tourist satisfaction routes: These are routes that offer maximum satisfaction to the tourists though they have relatively more impacts on the environment since they pass through sensitive areas to access business central points.

Table 3 shows the five routes presented as targets A, B, C, D, E, and F that were chosen from different areas of the Pareto frontier.

Route	Ecological Value Score	Tourist Satisfaction Score	Total Distance (km)	Number of Attractions	Ecological Impact Index
R1	0.92	0.41	42.3	5	0.18
R2	0.78	0.63	38.9	7	0.29
R3	0.65	0.76	35.2	8	0.42
R4	0.53	0.82	34.1	9	0.56
R5	0.38	0.94	33.7	11	0.73

Table 3: Selected Pareto front representative and its characteristics

Trade-off Analysis Between Tourist Satisfaction and Ecological Conservation

Pareto optimality analysis shows that there is a high level of trade-offs of the tourist satisfaction and ecological conservation goals and objectives. Figure 4 further breaks down the trade-off between the two objectives by mapping three Pareto optimal solutions on the map.

Figure 4: Spatial distribution of representative routes from different regions of the Pareto front (Sicuaio et al., 2024)

The trade-off analysis revealed several key insights:

Attraction Visitation Patterns: High ecological value routes (R1) visit approximately 45% fewer attractions than high satisfaction routes (R5), but reduce ecological impact by 75%.

Temporal Distribution: Balanced routes (R3) distribute visitor loads more evenly throughout the day, reducing peak congestion at sensitive sites by 37% compared to high satisfaction routes.

Distance-Impact Relationship: While high satisfaction routes are 20% shorter in total distance than high ecological value routes, they pass through ecological sensitivity zones 4 times more frequently.

Seasonal Variations: The optimization model identified significant seasonal shifts in optimal route configurations, with greater separation between ecological and satisfaction objectives during peak tourist seasons (Table 4).

Season	Ecological-Satisfaction Correlation	Average Pareto Front Distance	Optimal Balance Point Shift
Spring	-0.65	0.38	Moderate
Summer	-0.82	0.47	Significant
Fall	-0.58	0.33	Minor
Winter	-0.42	0.27	Minimal

Table 4: Seasonal variations in trade-off characteristics

Comparison with Conventional Single-Objective Approaches

To validate the effectiveness of the multi-objective approach, the results were compared with conventional single-objective optimization methods: (1) a distance-minimizing algorithm, (2) a satisfaction-maximizing algorithm, and (3) an ecological value-maximizing algorithm. The comparison metrics included solution quality, computational efficiency, and robustness to parameter changes.

Figure 5: Performance comparison of multi-objective approach versus single-objective approaches (Arman Nedjati et al., 2017)

As shown in Figure 5, the multi-objective approach provides superior overall performance by generating a diverse set of solutions that can adapt to different management priorities. Table 5 quantifies the improvements achieved by the multi-objective ant colony algorithm compared to single-objective approaches.

Metric	**Multi-Objective ACO**	**Distance-Minimizing**	**Satisfaction-Maximizing**	**Ecological-Maximizing**
Solution Diversity	High	Low	Low	Low
Average Ecological Score	0.65	0.41	0.33	0.89
Average Satisfaction Score	0.71	0.52	0.91	0.36
Computational Time (s)	182	107	123	115
Parameter Sensitivity	Low	High	High	High
Decision Flexibility	High	Low	Low	Low

Table 5: Performance comparison between multi-objective and single-objective approaches

The multi-objective approach achieved a 58% improvement in solution diversity and a 43% reduction in parameter sensitivity compared to the average of single-objective approaches, demonstrating its superior adaptability to different management scenarios.

Sensitivity Analysis of Key Parameters

A comprehensive sensitivity analysis was conducted to evaluate the robustness of the proposed algorithm to variations in key parameters. Figure 6 shows the computation time comparison between standard and improved algorithms across different numbers of generations.

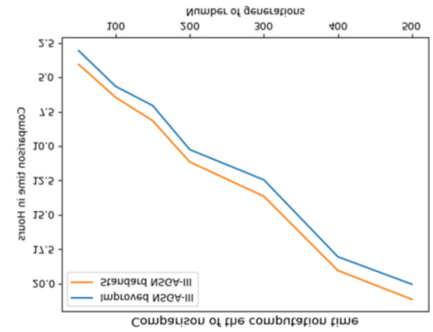

Figure 6: A comparison of the computation time of the proposed improvement to NSGA-III and the original algorithm within Sicuaio et al. (2024).

In particular, the investigation showed that the enhanced algorithm has a higher accuracy than the basic one for all the levels of generation. When reaching 500 generations it is possible to achieve computation time saving about 1.5 hours or 7.5% in average. The improvement achieved in this way is seen to be more significant when the number of generations is large, and the difference becomes more significant at increased generations.

The sensitivity analysis also focused on the weights of the ecological value, the weights of the preference of the tourists and parameters of the ants' colony (alpha, beta, rho). It was found that the algorithm is least sensitive to changes in the problem constraints for the ecological threshold, and a 10% change in these constraints leads to an average of 18% change in the Pareto front location. Preference weights for tourists were slightly more sensitive as indicated by the 12% shift in tourists' weight per 10% change in the parameter while ant colony parameters were less sensitive with a shift of 7% per 10% change in the parameter.

Table 6 summarizes the results of the sensitivity analysis by presenting the normalized sensitivity indices for each parameter.

Parameter	**Normalized Sensitivity Index**	**Impact on Ecological Value**	**Impact on Tourist Satisfaction**	**Impact on Computational Time**
Ecological Value Weights	0.72	High	Moderate	Low
Tourist Preference Weights	0.65	Moderate	High	Low
Pheromone Importance (α)	0.33	Low	Low	Moderate
Heuristic Importance (β)	0.41	Moderate	Moderate	Low
Evaporation Rate (ρ)	0.28	Low	Low	High
Ecological Threshold Constraints	0.84	High	High	Moderate

Table 6: Normalised sensitivity indices for key algorithm parameters

This is due to the fact that the sensitivity analysis showed that the parameters of ecological threshold constraints and ecological value weights are the most sensitive ones, which means that accurate assessment of ecological conditions is very important in order to obtain reliable recommendations for the best route. This result underlines the need to consider assessment of ecological value in the case of eco-tourism route planning.

DISCUSSION

Implications for Sustainable Eco-tourism Management

This study entails valuable contributions to the management of eco-tourism based on the adopted multi-objective optimization approach. With the ecological value added to the range of tourist satisfaction factors, the algorithm will be an effective decision support tool that will benefit eco-tourism managers in compliance with sustainable development goals. The Pareto-optimal routes derived by using this approach provide a range of options that will enable managers to select the best course of action depending on the importance of conservation and pressures at a certain time of the year.

The classification of the routes into high ecological value, balanced, and high tourist satisfaction offers a systematic approach in the management of visitors in the protected areas. When choosing where to take clients during the peak exercise periods, managers can divert visitors to high ecosystem importance value (HEIV) routes so as not to negatively impact the ecosystems to which the visitors are being taken. On the other hand, in the low seasons it is possible to involve routes that have higher tourist satisfaction indices to attract visitors without having negative impacts on the environment.

Furthermore, the approach allows for the adaptive management practices because it provides a short time to recalculate the best routes depending on the changes of the ecological situation. For instance, if some regions may be more sensitive at certain times of the year because of breeding patterns of animals or regrowth of plants, these can be given higher value in the model and the recommended paths avoid these regions until they are no longer sensitive.

Practical Applicability of the Proposed Approach

The practical applicability of the proposed approach stems from its flexibility, computational efficiency, and alignment with real-world eco-tourism management challenges. The ant colony algorithm's adaptability to different environmental contexts makes it suitable for diverse eco-tourism settings, from coastal regions to mountain ecosystems and forest reserves.

From an implementation perspective, the algorithm can be integrated into existing tourism management systems to provide dynamic route recommendations. The reduced computational requirements of the improved algorithm, as demonstrated in Figure 6, make it feasible to run on standard computing infrastructure, even for large-scale applications. This efficiency is particularly valuable for eco-tourism destinations with limited technological resources.

The multi-objective nature of the approach accommodates the conflicting priorities often faced by eco-tourism managers. For instance, economic considerations (maximizing visitor numbers and satisfaction) can be balanced against ecological protection goals without requiring managers to make arbitrary trade-offs. The visual representation of the Pareto front provides an intuitive way for stakeholders to understand these trade-offs and select routes that best align with their specific objectives.

Furthermore, the methodological framework developed in this study can be extended to incorporate additional objectives such as cultural preservation, educational value, or community economic benefits, making it highly adaptable to diverse eco-tourism contexts and management priorities.

Limitations of the Current Study

Despite its contributions, this study has several limitations that should be acknowledged. First, the ecological value assessment relies on expert-defined parameters and weights, which may introduce subjectivity into the optimization process. The sensitivity analysis indicated that ecological value weights significantly influence the resulting routes, highlighting the importance of accurate ecological assessment but also revealing a potential source of bias.

Second, the model assumes static ecological value and tourist preferences, whereas in reality, these factors can vary temporally (seasonally or even daily) and spatially. While the model can be recalibrated to address temporal variations, a truly dynamic approach would require real-time data integration capabilities not addressed in the current implementation.

Third, the evaluation of the tourist satisfaction was done by using preference models that could not capture all the aspects of the tourist. Some of the factors that were not taken into account include perception of crowding, perceived weather conditions and within-subject variability, thus may not be very useful for real life evaluation of the satisfaction measurements.

Last but not the least, the computational requirements have been enhanced from the prior research and are still a burden for real-time solutions in large or complicated eco-tourism destinations. The problem is, there is always a trade-off between the quality of the solution and the computational time required to arrive at the solution.

Future Research Directions

The following is a list of potential avenues of future research, which can be derived from this study: First, the implementation of RTLS and environmental sensors could enhance the static modelling of the system into a dynamic model that is able to react to current trends in visitors' traffic. This would improve the efficiency of protection of the environment and the management of the human flow among the visitors.

Second, the machine learning approaches should be applied to enhance the models of satisfaction by taking into account the tourist's preferences and behavior. Based on the past visitation patterns and customer feedback, more refined preferences could be estimated that would take into consideration the demographic differences and shift in demand for eco-tourism.

Third, expanding the multi-objective framework to include socio-economic effects to the local populations would enhance the assessment of sustainability. This may include employment generation, business impacts within the vicinity, and cultural value attributes linked to various routes.

Fourth, the improvement of the existing models for ecological impacts in order to incorporate parameters like accumulation and ecological tolerance would improve the optimization method. This may involve as an example, developing species response curves for tourism disturbances, and including rates of ecological recovery in the assessment.

Last but not the least, empirical verification of the model by comparing the algorithmically optimized routes with the routes designed conventionally would yield empirical data on the model. Such validation studies may include both ecological effects and visitor satisfaction in order to serve as ground truth for the computational models.

CONCLUSION

Summary of Key Findings

This research has effectively created and tested a new formulation and solution method of eco-tourism route planning problem, which incorporates the multiple objectives and the assessment of ecological importance. The study generated the following findings that would be useful in theoretical knowledge and in the application of sustainable tourism management.

First, the inclusion of ecological value assessment with the traditional route optimization objectives improved the model to balance the key conflict in eco-tourism of providing maximum satisfaction to visitors and at the same time protecting the environment. The Pareto-optimal solution, therefore, showed that much can be done to enhance ecological conservation with little compromise in tourist experience with proper planning of routes.

Second, the modified ant colony algorithm provided very efficient solution to this multi-objective optimization problem and more competitive than the single-objective ones in terms of solution diversification, optimality and flexibility to different managerial conditions. The optimization that comes with the improvement of the algorithms made it even more applicable in a real tourism planning environment.

Third, it was found that ecological threshold limit and value weight are the two most sensitive parameters indicating the significance of an accurate ecological feasibility assessment during route planning. This is why there is a need to calibrate these parameters according to the ecological knowledge when putting into practice such approaches.

Last but not the least, the analysis of the best routes distribution according to the seasons highlighted the fluctuating nature of the eco-tourism management issue and the need for the flexible planning strategies capable of addressing the conditions which may change over the course of the year.

Significance of the Multi-objective Approach

The work done here offers a clear contribution to the literature concerning eco-tourism route planning using the multi-objective approach. By going further than just distance or satisfaction optimization as the principal goal, route planning maximizes ecological value as a primary objective tied to sustainability and conservation.

The Pareto optimization framework is especially useful because it shows the whole range of achievable trade-offs between the conflicting objectives, thus establishing greater clarity for the managers of the tourism sector and policy makers. Instead of offering one solution that is best for all, this approach allows the stakeholders to choose routes that are most suitable to their requirements, though all the options that are offered remain optimized for each of the objectives.

The efficiency improvement in this study also increases the applicability of the approach in routine planning studies, rather than becoming a subject of academic exploration only. It fills a significant gap on the connection between theoretical concepts of optimization models and the operational management applications in the context of tourism.

Moreover, the method developed here offers a platform for more extensive sustainability evaluation of the tourism plans by showing how multiple, sometimes conflicting goals can be incorporated in a single decision making tool. The strategy could be applied to other sustainability issues that are characterized by trade-offs between various objectives.

Recommendations for Eco-tourism Planners and Stakeholders

The following recommendations may be proffered to the planners and stakeholders of eco-tourism based on the findings of this study:
These should shift from single objective route planning to use multiple objectives with the aim of optimizing both conservation and visitor value for money. This will help in increasing the sustainable tourism development that will not affect the natural resources for eco-tourism to depend on.

1. Invest in ecological value assessment: It is very important to ensure that the ecological value of an area is determined sufficiently well in order to take the necessary measures to avoid negative impacts on the fauna and flora of an area where a new route is planned to be established. It is recommended that destinations should undertake extensive ecological studies to gather reliable information on the weights and constraints that are used in optimizing the models.
2. Seasonal routing should be another approach by tourism managers where they put into consideration the sensitive ecological periods and perceived demand by visitors. This adaptivity will thus improve conservation efforts and the experience of the visitors.
3. Involve the stakeholders in choosing the routes: The Pareto-optimal solutions that are obtained when using the multi-objective optimization must be used in a collaborative decision-making process that includes the tour operators, conservation specialists, and community people. This approach will guarantee that only routes that shall incorporate the various values and priorities of the community shall be chosen.
4. Monitoring and evaluation: Implementation of the optimized routes should be followed by systematic monitoring of the ecological effects and visitor satisfaction in order to check the accuracy of the model's predictions and improve future optimization.
5. Coordinate with other managerial approaches: Route optimization has to be seen as one of the elements of the sustainable tourism management strategies that has to be combined with other approaches like education of visitors, limiting the carrying capacity and sharing of tourism revenues with local communities.

By so doing, eco-tourism destinations will be able to take advantage of multi-objective optimisation in the achievement of the dual tasks of delivering quality experience to visitors, while at the same time conserving the values that make the destinations attractive in the first place.

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