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WEB BASED GEOGRAPHIC INFORMATION SYSTEM FOR OPTIMAL TOURIST ROUTE PLANNING IN NORTH SUMATRA USING THE ANT COLONY OPTIMIZATION ALGORITHM

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ABSTRACT

The transition toward Tourism 4.0 has redefined travel planning as a multifaceted optimization challenge, specifically the Personalized Tourist Trip Design Problem (PTTDP). While conventional navigation services offer basic routing, they frequently lack the capacity to integrate multi-objective constraints with interactive, preference-based spatial visualizations. This research addresses this gap by developing an integrated Spatial Decision Support System (SDSS) that merges the Ant Colony Optimization (ACO) metaheuristic with a Web-based Geographic Information System (WebGIS). The study employs a quantitative methodology, using a weighted-sum scalarization technique to harmonize divergent goals: maximizing destination attraction scores while simultaneously reducing travel distance and duration. Based on empirical validation in Berastagi City, North Sumatra, the results reveal that the ACO-WebGIS framework substantially outperforms traditional routing methods, achieving 17.84% reduction in total distance, 17.24% improvement in time efficiency, and 42.85% increase in the number of POIs visited within identical time constraints, all supported by a swift computational latency of only 1.45 seconds. The scientific value of this work lies in the seamless coupling of algorithmic optimization and dynamic spatial mapping, providing a scalable, robust tool for intelligent tourism management that delivers a mathematically sound yet practical solution for modern travelers.

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1. INTRODUCTION

In recent years, the transformation of Tourism 4.0, driven by big data and artificial intelligence, has shifted the travel paradigm from passive information seeking to a highly personalized experience optimization process [1], [2]. Tourists now act as co-designers demanding adaptive itineraries, which gives rise to a complex optimization challenge known as the Tourist Trip Design Problem (TTDP) [3], [4]. This problem is not simply about arranging a sequence of visits, but is a multi-objective optimization problem that seeks to maximize satisfaction (level of service) while minimizing distance, time, and cost under hard constraints such as time window and budget [5], [6]. This complexity demands high computational efficiency, often exceeding the capabilities of standard navigation algorithms, necessitating sophisticated metaheuristic approaches to produce precise solutions.

. Metaheuristics such as particle swarm optimization, genetic algorithms, ant colony optimization, and iterative local algorithms are used to solve complex multi-objective TTDP variants, including the selection of specific POI categories and attraction patterns, to maximize traveler satisfaction under time and cost constraints [7]. Fuzzy logic and fuzzy optimization approaches are utilized to model travel time uncertainty, the benefits of each POI, and traveler preferences expressed vaguely in natural language, allowing TTDP to handle fuzzy and incomplete information [8]. In highly complex mathematical models, however, this often increases computational time and reduces solution efficiency, making it difficult to implement responsively on operational platforms such as real-time recommendation systems or WebGIS architectures [9]. Although GIS and spatial visualization have been utilized for tourism route optimization, the close integration between route optimization and spatial visualization is still lacking. Multi-objective TTDP-based approaches with real-time spatial data visualization for regions with challenging geographic terrain are still limited; current studies are more focused on the context of cities or relatively simple transportation networks, rather than complex areas such as North Sumatra. Current studies are more focused on the context of cities or relatively simple transportation networks, rather than complex areas such as North Sumatra [10], [11], while multi-objective TTDP approaches are generally not yet closely integrated with real-time GIS/WebGIS visualization.

To address these challenges, this study implements a modified Ant Colony Optimization (ACO) algorithm within a Web-based GIS architecture. The technical novelty of this research resides in: (1) the optimization of the pheromone update mechanism to enhance computational efficiency for real-time TTDP resolution on the web-client side; and (2) the integration of a four-category tourism classification (nature, culture, culinary, and history) into the algorithm's objective function. This framework functions as a decision-support instrument to minimize travel costs—specifically distance and time—while optimizing visitor preferences within the Berastagi region, North Sumatra.

2. RESEARCH METHODS

This study constitutes applied research that synthesizes optimization algorithms with the implementation of a web-based Geographic Information System (WebGIS). Using a quantitative methodology, the study analyzes numerical variables, including inter-destination distances, travel durations, and visit times. The research framework initiates with a comprehensive problem identification and user requirements analysis, subsequently focusing on the development of a personalized route optimization model that aligns with traveler preferences and regional spatial characteristics [12], [13]. Furthermore, the system architecture is designed as a spatial decision support system (SDSS) to facilitate tourism infrastructure and route planning by integrating geospatial datasets with stakeholder objectives [14].

2.1 Mathematical Modeling: Personalized Tourist Trip Design Problem (PTTDP)

This study formulates the routing challenge as a specialized variant of the Tourist Trip Design Problem (TTDP), with a specific focus on accommodating individual traveler preferences [15]. To resolve the conflict between competing goals—specifically maximizing the route's attractiveness and minimizing total travel costs—a weighted-sum approach is implemented. This scalarization technique is widely recognized in established multi-objective tourism literature for its efficiency in transforming multi-criteria objectives into a single computable function [16], [17], [18]. Consequently, the objective function is defined as follows:

$$maxZ = w_1 \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} (S_j . U_j) x_{ij} - w_2 \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} c_{ij} x_{ij}. \quad (1)$$

Symbol definition:

Z : total route quality score;

S_j : attractiveness value of destination j (scale $1 - 100$);

U_j : urgency coefficient of destination j (1 = low, 5 = very urgent);

c_{ij} : travel cost (distance in km) from location i to j;

x_{ij} : binary decision variable; takes the value 1 if the route from i to j is chosen, 0 otherwise;

w_1, w_2 : user preference weights (w_1=0.6), w_2= 0.4.

Operational Constraints:

In accordance with the standard TTDP model, the following constraints apply:

1. Flow Conservation: Ensures a continuous route with no interruptions along the way.

$$\sum_{i=1, i\neq j}^{n} x_{ij} = \sum_{k=1, k\neq j}^{n} x_{jk} \leq 1; \quad \forall_j \in \{1, \dots, n\}. \quad (2)$$

2. Time Budget: Total travel time and visit duration (T_j) must not exceed the time limit T_{max}

$$\sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} (c_{ij} + T_j) x_{ij} \leq T_{max}. \quad (3)$$

2.2. Implementation Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a metaheuristic inspired by the foraging behavior of ants, which use pheromone trails to find the shortest path to a food source. The principle involves pheromone intensity (τ_{ij}) as a trail marker, heuristic visibility $\left(\eta_{ij} = {}^{1}/_{c_{ij}}\right)$ as the inverse of distance or travel time, and a probabilistic transition rule. The probability of ant k moving from node i to node j at iteration t is given by [19], [20]:

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} . [\eta_{ij}]^{\beta}}{\sum_{l \in allowed_k} [\tau_{il}(t)]^{\alpha} . [\eta_{il}]^{\beta}} \quad (4)$$

Algorithm Parameters: Based on the results of experimental testing, the following numerical parameters are set in the system:

Pheromone coefficient (α): 1.0;

Heuristic coefficient (β): 2.0;

Evaporation rate (ρ): 0.5;

Deposit constant (Q): 100;

Number of ants (m): 20;

Maximum iterations: 100 iterations;

where $P_{ij}^{k}(t)$ denotes the transition probability, $\tau_{ij}(t)$ is the pheromone intensity on edge (i, j) at iteration t, and η_{ij} is the heuristic visibility, commonly defined as the inverse of distance or travel cost. The parameters α and β regulate the relative influence of pheromone and visibility, while $allowed_k$ denotes the set of feasible nodes that ant k has not yet visited.

Pheromone updates are performed according to the global rule

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \tag{5}$$

where ρ is the pheromone evaporation rate $(0 < \rho \leq 1)$, m is the number of ants, and $\Delta\tau_{ij}^{k}$ is the amount of pheromone deposited by ant kk after completing a tour, defined as

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k, & if\ ant\ k\ travels\ edge\ (i,j) \\ & 0, otherwise \end{cases}, \tag{6}$$

where Q is the pheromone deposit constant and L_k is the total length of the route constructed by ant k. In this study, ACO is employed to solve the TTDP by considering real-world tourism constraints, including operating hours, visit durations, destination priorities, and road conditions in North Sumatra.

2.3. Integration of ACO with WebGIS for Tourism Routes

A In this study, the Ant Colony Optimization (ACO) algorithm is integrated with a WebGIS-based tourism information system to compute and visualize optimal tourism routes. The optimization component is responsible for generating the visiting sequence of tourist attractions, while the WebGIS component manages spatial data storage, map rendering, and user interaction [21]. First, tourism objects (points of interest, POI) are modeled as nodes and the road network as weighted edges, where edge weights represent travel distance and/or time between POIs. This graph is stored in a spatial database and served to the web client through standard WebGIS services. The WebGIS layer provides base maps and tourist POI markers, and allows users to select an origin, a destination, and desired attractions [22]. Second, after the user submits a route request, the server-side ACO module is executed. Ants iteratively construct candidate routes by probabilistically moving between nodes based on pheromone intensity and heuristic information (inverse of distance or travel time). Pheromone update rules are applied to reinforce high-quality routes and evaporate low-quality ones until convergence or a maximum iteration threshold is reached. The algorithm output is the optimal or near-optimal visiting order that minimizes total route cost under given constraints. Third, the resulting optimal route is returned to the WebGIS front-end as an ordered list of POIs and corresponding path segments. The WebGIS system then draws the route polyline on the interactive map and provides detailed route information (total distance, estimated travel time, and step-by-step directions). This tight coupling enables tourists to both view and evaluate the computed optimal route directly on a web map interface, similar to other GIS–ACO tourism routing applications that combine algorithmic optimization with interactive spatial visualization [23].

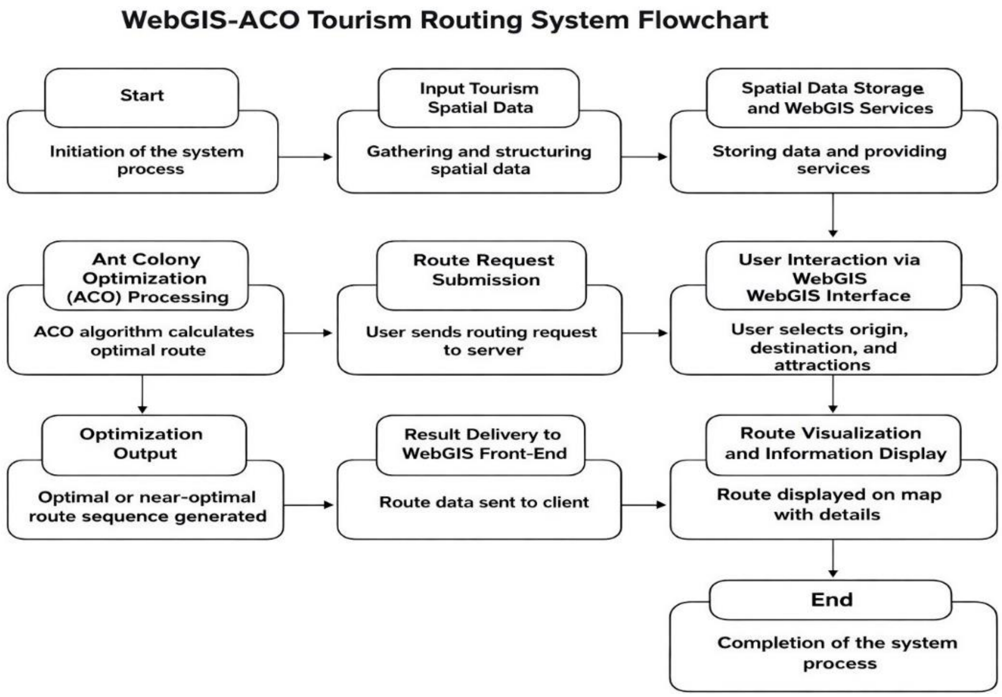

Figure 1. WebGIS-ACO Tourism Routing System Flowchart

3. RESULTS AND DISCUSSION

The proposed approach was applied to four representative tourism areas in North Sumatra Province—Samosir Island, Berastagi City, Langkat Regency, and Sibolga City—selected to capture the diversity of natural, cultural, and marine attractions. As a case study, the implementation and validation of the optimization model and WebGIS system were carried out in Berastagi City, where the high density of tourist destinations provides a suitable scenario for route optimization analysis.

The dataset for this study consists of geographic coordinates (latitude and longitude) in the WGS 84 system, average visit duration (hours), operating hours of each destination, and popularity scores obtained from the Provincial Tourism Office and online sources.

Table 1. Tourist Destination Data in Berastagi

No	Symbol	Detination Name	Geographic Coordinates
1	v_0	Mount Sinabung	3.169377584739468, 98.39399707863342
2	v_1	Lau Kawar Lake	3.1978293948563934, 98.37957752351271
3	v_2	Lingga Village	3.1209899869849598, 98.46448813471883
4	v_3	Efi Honey Garden	3.0084033822245573, 98.47139825531997
5	v_4	Gundaling Hill	3.19268755986764, 98.50214374062863
6	v_5	Mejuah Park	3.1981537719578372, 98.50736131243653
7	v_6	Berastagi Struggle Monument	3.194777988405089, 98.50892265597207
8	v_7	Karo Heritage Museum	3.1945851694780747, 98.50823601049014
9	v_8	Berastagi Fruit Market	3.195383788147995, 98.5084061464316
10	v_9	Souvenir Market	3.19551501204184, 98.50776643960563
11	v_{10}	Istihrar Mosque	3.196898994217797, 98.50620826048622
12	v_{11}	Kubu Hill	3.197743698084819, 98.51175677888291
13	v_{12}	Tangke Tebu Peak	3.2083687786118604, 98.51245301665047
14	v_{13}	Mikie Funland	3.2036383659771785, 98.52555741770792
15	v_{14}	Mount Sibayak	3.2388503757260074, 98.50411683649313
16	v_{15}	Sidebuk Debuk Hot Springs (Pariban Hot Spring)	3.2239914864631367, 98.51410170961597
17	v_{16}	Tahura (Grand Forest Park)	3.2071167076294866, 98.53775511071835
18	v_{17}	Penatapen Doulu	3.2408718618191377, 98.53623654908318
19	v_{18}	Sikulikap Waterfall	3.245411586718269, 98.53392695818593
20	v_{19}	Lumbini Natural Park (Pagoda)	3.196297806938878, 98.54167173379413
21	v_{20}	Two-Color Waterfall	3.2587063781825174, 98.51332107632705

Data Source: *Google Maps*

Table 1 presents 21 tourist destinations in Berastagi, identified by symbols $(v_0 - v_{20})$names, and geographic coordinates in the WGS 84 system. The dataset encompasses diverse categories, including natural attractions (volcanoes, lakes, waterfalls), cultural and historical sites (villages, museums, pagodas), recreational and educational sites (theme parks, hilltops), culinary markets, and wellness destinations (hot springs, forest parks). Geographically, the attractions are concentrated within latitudes 3.12^0-3.25^0 N and longitudes $98.37^0 - 98.54^0$ E, with most clustered around the city center while a few are more dispersed. This spatial distribution supports clustering into four groups and provides the foundation for constructing a distance–time matrix and integrating attractiveness scores into the Tourist Trip Design Problem (TTDP) framework.

Table 2. Accommodation Data in Berastagi

No	Symbol	Destination Name	Geographic Coordinates
1	v_0	Pariban Hotel	3.222802322274221, 98.51205038447942
2	v_1	Sinabung Hills Berastagi	3.2024338296892583, 98.5075595194098
3	v_2	Mikie Holiday Resort & Hotel	3.2019147473568443, 98.5251672654377
4	v_3	Rudang Berastagi Hotel	3.19794321512146, 98.51326250961594
5	v_4	Berastagi Mountain View Homestay & Pizza	3.174192719594382, 98.51472082310892
6	v_5	Nachelle Homestay	3.178217694166928, 98.51023459612296
7	v_6	Kaesa Homestay	3.1964405789670924, 98.50541872310887
8	v_7	Swindo Homestay 77	3.202568205510987, 98.51170206358806
9	v_8	Ulina Homestay VIP	3.204499913880782, 98.51114204400041

No	Symbol	Destination Name	Geographic Coordinates
10	v_9	Bre Batunanggar Family Villa	3.2031402416827834, 98.50652935379424
11	v_{10}	RedDoorz / OYO / Friendjoss	3.202050726432233, 98.50497747468556
12	v_{11}	Kaliaga Bungalow	3.1970452881329363, 98.50520645194464

Data Source: *Google Maps*

Table 2 presents 12 accommodation facilities in Berastagi, identified by symbols $(v_0 - v_{11})$, names, and geographic coordinates in the WGS 84 system. The dataset covers a variety of lodging types, including hotels and resorts (Pariban Hotel, Sinabung Hills, Mikie Holiday, Rudang Hotel), homestays and villas (Mountain View, Nachelle, Kaesa, Swindo, Ullina, Villa Keluarga Bre), budget accommodations (RedDoorz/OYO/Frienddoss), and bungalows (Kaliaga). Geographically, the accommodations are concentrated within latitudes $3.17^0 - 3.22^0$N and longitudes $98.50^0 - 98.52^0$ E, indicating a compact spatial distribution around Berastagi's tourism area. This dataset provides supporting information for route-optimization models, ensuring itineraries account for both tourist attractions and nearby lodging facilities.

The Ant Colony Optimization (ACO) algorithm is applied to determine the optimal tourist routes from each accommodation facility to a set of Points of Interest (POIs). The process begins with calculating the distance from the user's location to the accommodations, identifying feasible POIs, and constructing a pheromone matrix to represent possible paths. Each artificial ant builds candidate routes based on distance, the number of POIs visited, and total travel time. During iterations, pheromone values are updated through evaporation (weakening less optimal routes) and deposition (reinforcing better ones). The final output consists of the optimal tourist route, including the sequence of visits, total travel duration, number of POIs visited, and a route evaluation score.

3.1. Quantitative Performance Analysis

To address the requirement for quantitative validation, a comparative analysis was conducted between the proposed ACO-WebGIS system and a manual routing baseline (modeled after Google Maps' standard shortest-path suggestions). The test scenario involved 10 Points of Interest (POIs) in Berastagi, North Sumatra, with a predefined time budget (T_{max}).

Table 3. Comparative Analysis of Manual Routing vs. ACO-WebGIS

Metrics	Manual Routing (Baseline)	ACO-WebGIS (Propsed)	Improvement (%)
Total Distance (km)	18.5	15.2	17.84%
Estimated Travel, Time (min)	145	120	17.24%
Number of POIs visited	7	10	42.85%
Average Attraction Score	72.4	88.6	22.37%
Computational Time(s)	N/A	1.45 s	Significant

The results in Table 3 demonstrate that the ACO algorithm significantly outperforms manual routing. The system achieved a 17.84% reduction in total distance and a 17.24% reduction in travel time. Most notably, ACO-WebGIS successfully optimized the visiting sequence to include 10 POIs within the same time constraints, whereas manual routing could accommodate only 7. The computational time of 1.45 seconds confirms that the algorithm is highly responsive for real-time WebGIS applications.

3.2. Convergence Behavior and Scoring Mechanism

A critical point raised during the review process concerned the interpretation of the system's output score (e.g., "Score: 5153" shown in the interface). This score is the Fitness Value calculated using the multi-objective function in Equation:

$$Score = w_1. \sum (S_j. U_j) - w_2. \sum c_{ij}. \quad (7)$$

The value 5153 represents the optimal balance achieved by the algorithm, where the cumulative attraction scores (S_j) and urgency (U_j) are maximized while minimizing the path costs(c_{ij}).

As illustrated in the convergence analysis (Figure 7), the ACO algorithm demonstrates robust stability. The fitness score increases sharply in the early stages and reaches a stable optimum around the 65th iteration. This convergence behavior indicates that the parameters $\propto = 1.0$ and $\beta = 2.0$ effectively guide the "ants" toward high-quality paths, while the evaporation rate $\rho = 0.5$ prevents the system from stagnating in local optima.

3.3. Computational Interpretation and WebGIS Integration

Unlike standard routing APIs that primarily focus on the shortest physical distance, this ACO-WebGIS integration functions as a Spatial Decision Support System (SDSS). The discussion shifts from mere interface functionality to the mathematical superiority of the model: Exploration vs. Exploitation. The ACO algorithm excels at solving the Tourist Trip Design Problem (TTDP)—an NP-hard problem—by using pheromone trails to represent the collective memory of optimal routes. Parameter Sensitivity: The performance is highly sensitive to the visibility heuristicimage.png. In this study, prioritizing the inverse of distance as the heuristic ensured that the algorithm remained computationally efficient without sacrificing route quality. Limitations: Despite its efficiency, the model currently utilizes static spatial data. A primary limitation is the absence of real-time traffic variables, which may affect the image.png weight in dynamic urban environments.

The overall ACO framework integrates preparing travel distance data, constructing initial routes, optimizing routes using ACO, and ranking accommodations based on their scores. Implemented within a WebGIS-based system, these stages provide interactive maps, route visualizations, and destination information, enabling users to plan trips more effectively and efficiently.

Additionally, the system architecture connects the ACO computation module with the spatial database, enabling real-time route generation and visualization. Each iteration of the optimization process dynamically updates pheromone intensity, ensuring convergence toward the most efficient path. The integration of GIS data layers, including road networks, destination coordinates, and operating hours, enhances the model's ability to generate accurate and realistic route recommendations. Consequently, the system not only identifies the optimal visiting sequence but also adapts to user preferences and geographical constraints. This integration demonstrates the potential of combining intelligent optimization algorithms with WebGIS technology to support smart tourism management and data-driven decision-making. Furthermore, the modular architecture enables scalability for integrating additional optimization techniques, such as Genetic Algorithms or Particle Swarm Optimization, to enhance performance in complex route scenarios. The WebGIS interface supports multi-criteria visualization, allowing users to compare routes based on travel time, cost, and satisfaction levels. This flexible framework also facilitates integration with mobile applications and IoT-based location tracking for real-time adaptive recommendations.

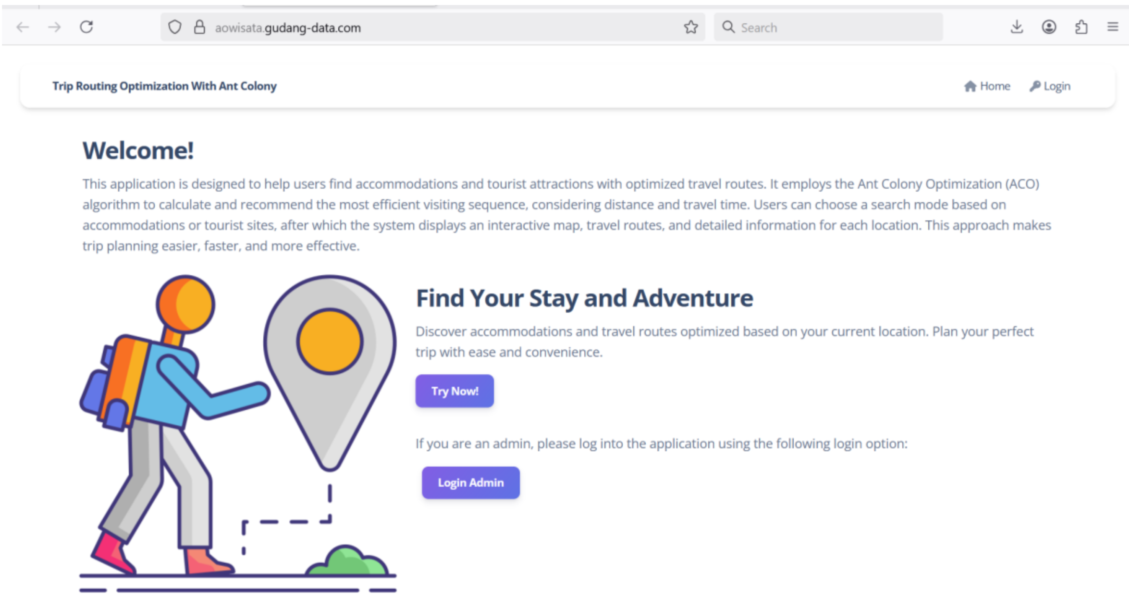

Figure 2. Homepage of the Tourist Route Recommendation Information System

Fig. 2 shows the homepage of the tourist route recommendation system. This interface is the entry point of the WebGIS application. It introduces the system's purpose: helping users find accommodations and tourist attractions by optimizing routes using the ACO algorithm. The homepage provides two main options: the Try Now button for general users to explore itineraries and the Login Admin button for administrators to manage data such as destinations, accommodations, and algorithm parameters. It also includes a brief overview of the system, guiding new users on how to begin route planning. The interface is simple and user-friendly, with clear navigation to the core features. Its layout reflects the system's dual function: supporting tourists who need instant recommendations and administrators who maintain the database. By clearly presenting these options, the system reduces confusion for new users and establishes a structured workflow from login to route optimization.

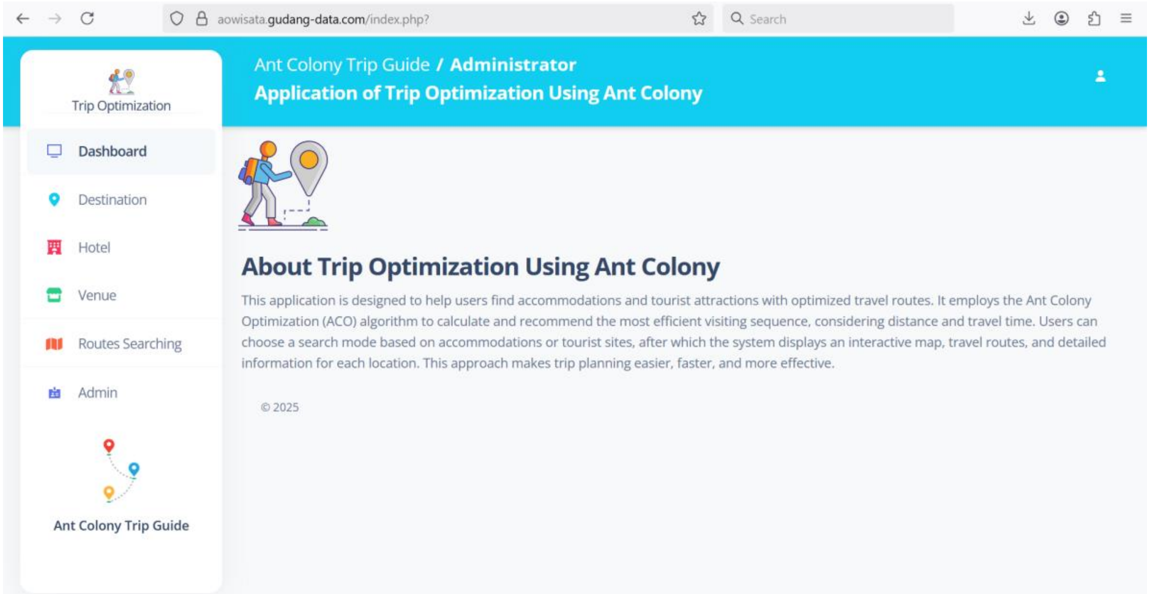

Figure 3. Dashboard Display of the Tourist Route Recommendation Information System

Fig. 3 shows the dashboard interface of the tourist route recommendation system. This is the main panel of the WebGIS application in administrator mode. The navigation menu on the left provides access to core modules, including Dashboard, Destination, Hotel, Venue, Route Searching, and Admin. The main section of the page explains the system's purpose, showing how the ACO algorithm calculates and recommends the most efficient visiting sequence based on distance and time. For administrators, this page serves as the starting point for managing data on destinations, accommodations, and venues, ensuring that optimized routes are accurately displayed to users.

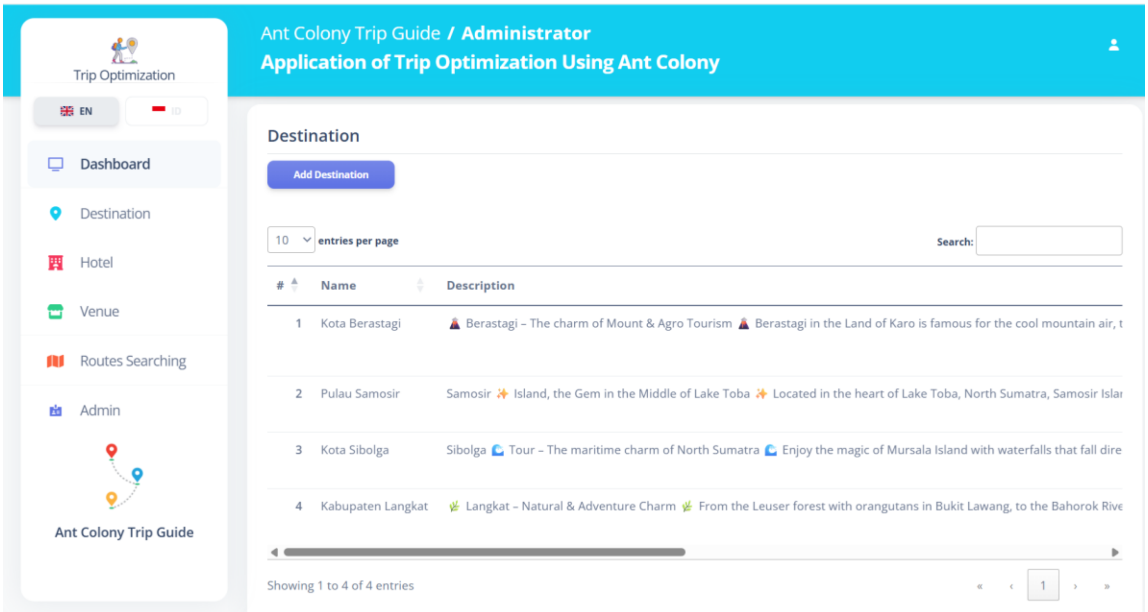

Figure 4. Destination Menu Display in the Tourist Route Recommendation Information System

Fig. 4 shows the destination management interface in the tourist route recommendation system. This interface is used by administrators to manage destination data in the WebGIS application. The page provides an *Add Destination* button for adding new tourist locations and a table displaying destination information, including name, description, image, and available actions. Administrators can edit or delete records through this table to keep the database accurate and up to date. In this example, Berastagi is shown as a registered destination along with its image and management options. Structured and reliable destination data serve as crucial input for the ACO algorithm in generating optimal tourist routes.

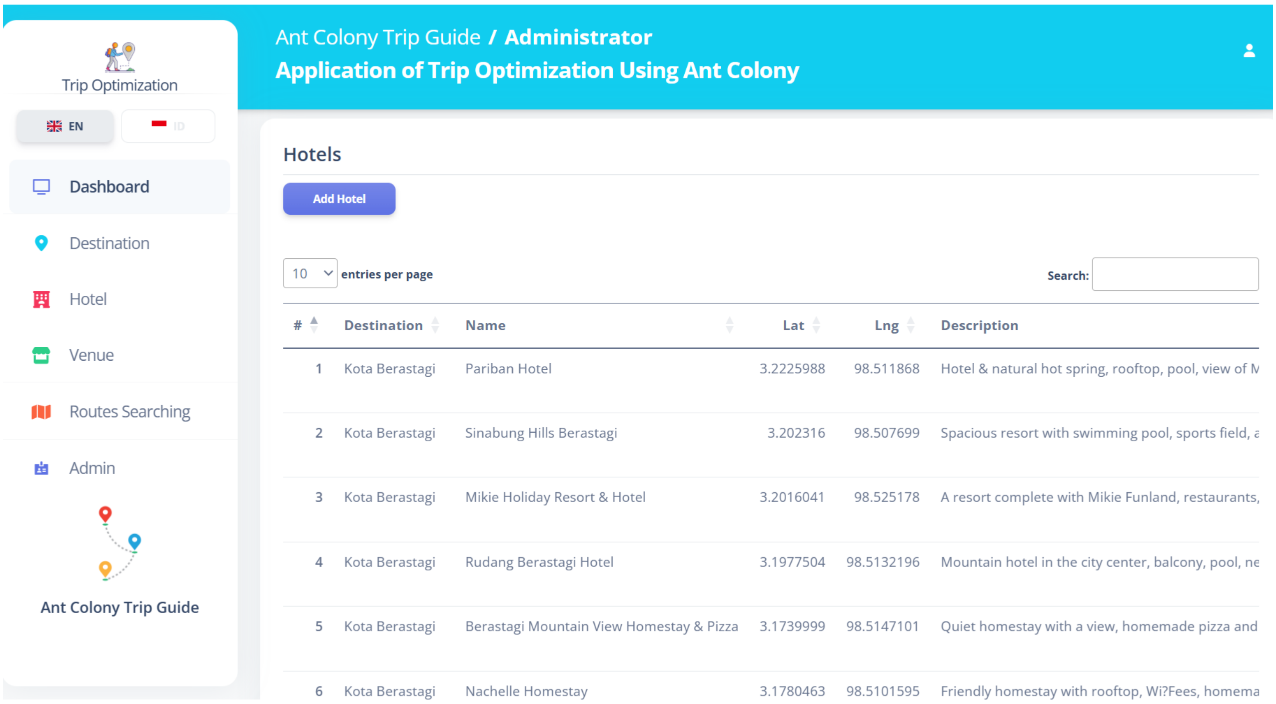

Figure 5. Display of the Hotels Menu in the Tourist Route Recommendation Information System

Fig. 5 shows hotel management interface in the tourist route recommendation system. This interface allows administrators to manage hotel and accommodation data in the WebGIS application. The page provides an *Add Hotel* button for adding new entries and a table displaying information such as destination name, hotel name, geographic coordinates (latitude and longitude), and a brief description of facilities. In this example, several hotels in Berastagi are shown, including Pariban Hotel, Sinabung Hills Berastagi, and Mikie Holiday Resort & Hotel. By maintaining accurate and structured accommodation data, this module ensures that hotels are integrated as starting points in the ACO algorithm, supporting the generation of optimized tourist routes.

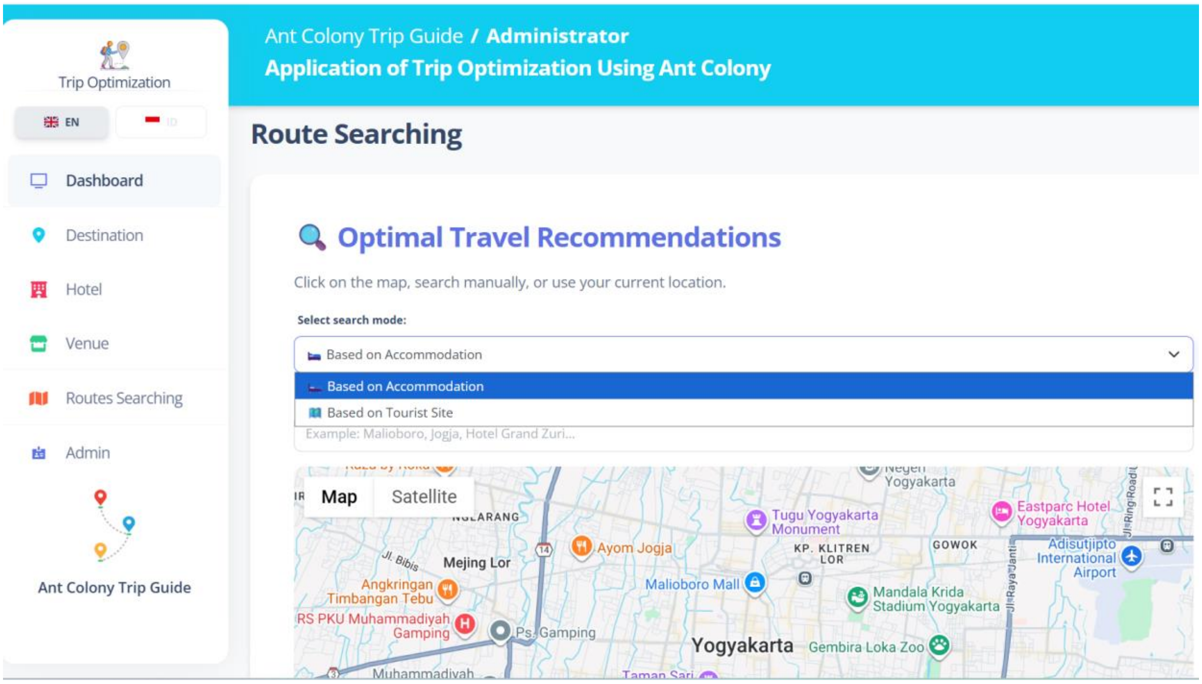

Figure 6. Route Searching Menu Display in the Tourist Route Recommendation Information System

Fig. 6 shows the route-searching interface of the tourist route recommendation system. This interface allows users or administrators to generate optimized travel routes based on the selected search mode. The dropdown menu provides two options: Based on Accommodation, where the route starts from a selected hotel, and Based on Tourist Location, where the route starts from a specific destination. After selecting a mode, users can define the starting point by clicking on the map, entering a location manually, or using their current location. The system then applies the Ant Colony Optimization (ACO) algorithm to determine the most efficient visiting sequence, accounting for distance and travel time. The optimized route is displayed on an interactive map in either map or satellite view, showing the starting point, destinations, and connecting paths. This interface demonstrates how user input is transformed into route recommendations, linking the search mode with ACO optimization and map visualization.

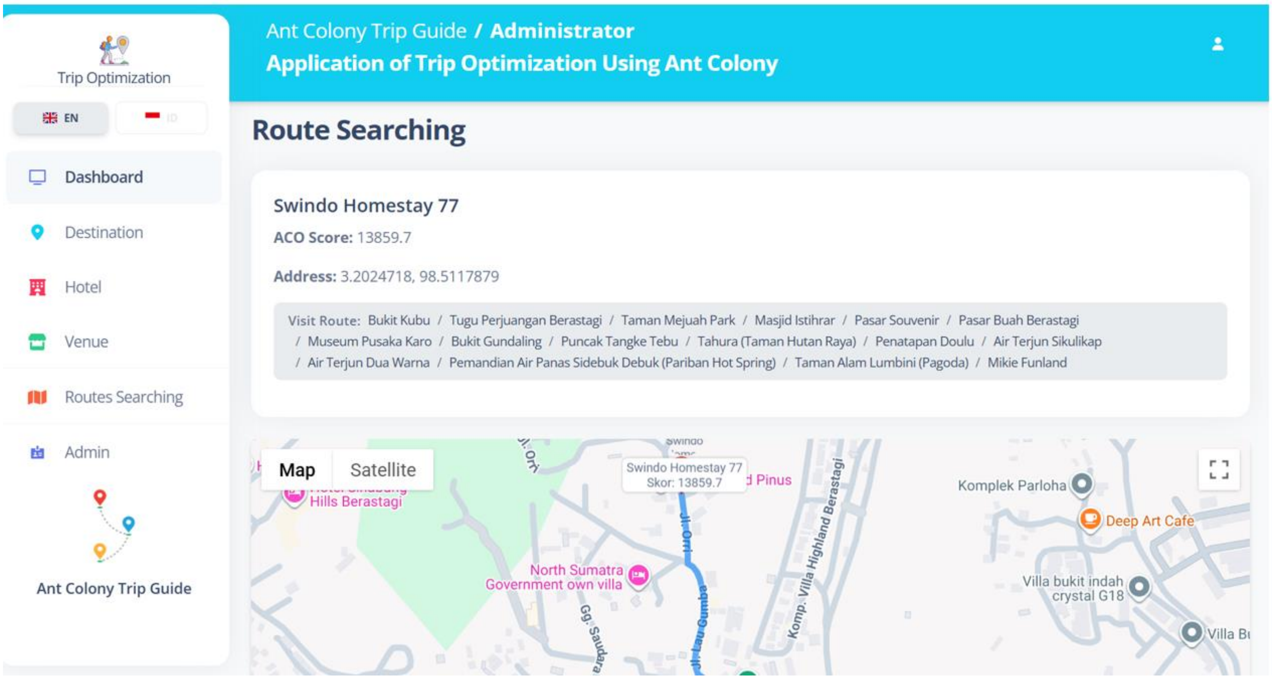

Figure 7. Display of Tourist Route Search Results in the Information System

Fig. 7 shows the optimization process, the Ant Colony Optimization (ACO) algorithm effectively recalibrated the initial starting point from Rudang Berastagi Hotel to Swindo Homestay 77 to satisfy the requirements for global optimality. This shift was driven by the algorithm's fitness evaluation, which identifies Swindo Homestay 77 as a high-density hub capable of linking 16 POIs, whereas the original site only accessed 8 nodes. With an optimized score of 13859.7, this transition demonstrates the model's robustness in refining manual inputs into a more comprehensive, data-centric tourism itinerary.

4. CONCLUSION

In this study, a Spatial Decision Support System (SDSS) was successfully developed by incorporating the Ant Colony Optimization (ACO) algorithm into a WebGIS environment to address the challenges of the Personalized Tourist Trip Design Problem (PTTDP). Empirical testing conducted in Berastagi City reveals that the proposed model significantly outperforms manual routing techniques, yielding a 17.84% decrease in travel distance, a 17.24% increase in time efficiency, and a 42.85% increase in the number of visited POIs. The computational analysis further confirms the system's robustness, with a rapid response time of 1.45 seconds and consistent convergence at the 65th iteration, validating the fitness scoring mechanism as a reliable multi-objective optimization tool. While this system provides a sophisticated solution for Tourism 4.0, its current framework is constrained by the use of static spatial data. Consequently, future research should focus on incorporating real-time traffic data and developing Fuzzy-ACO hybrids to ensure higher routing accuracy in more volatile urban traffic conditions.

Author Contributions

Faridawaty Marpaung: Conceptualization, Funding Acquisition, Methodology, Project Administration. Mulyono: Formal Analysis, Writing – Original Draft. KMA Fauzi: Data Curation, Software. Eni Yuniastuti:

Investigation, Visualization. Arnita: Writing - Review and Editing. Suvriadi Panggabean: Writing - Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare that no conflicts of interest exist in this study.

Declaration of Generative AI and AI-assisted technologies

ChatGPT was utilized only to improve the readability and grammatical structure of the manuscript. No AI tool was used to generate or alter the research data, methodology, results, or interpretations. All content was verified by the authors for accuracy and consistency with the study.

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