EFFICIENT ROUTE PLANNING FOR CONSERVATION TOURISM IN THE MEKONG

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ABSTRACT
Purpose: This study develops an efficient route planning model for conservation tourism across 80 destinations in the Mekong region, spanning Thailand and the Lao People's Democratic Republic (PDR). The research aims to minimize travel distance and cost while promoting sustainable tourism practices.
Design/methodology/approach: The study employs the Nearest Neighbours Heuristic (NNH) and Local Search Optimization techniques to identify the shortest routes, comparing their performance with the traditional Traveling Salesman Problem (TSP) approach. Location coordinates were collected within the study area, and the optimized routes were further enhanced by integrating Dynamic pricing and AI-driven forecasting.
Findings: The proposed method significantly reduces travel distance compared to the TSP approach. Incorporating Dynamic pricing and AI forecasting enables effective cost management and supports balanced distribution of tourist flows throughout the year, contributing to sustainable tourism in the Mekong region.
Research limitations/implications (if applicable): This study focuses on a specific geographic area, which may limit the generalizability of the proposed model. Future research could expand the framework to larger regions and incorporate multimodal transport considerations.
Practical implications (if applicable): The proposed route-planning model provides a practical tool for tourism planners and policymakers to improve conservation tourism efficiency, reduce operational costs, and promote environmentally responsible travel practices.
Originality/value: This research introduces an innovative integration of heuristic optimization techniques, dynamic pricing, and AI forecasting to support efficient and sustainable tourism route planning. It offers a replicable model for other conservation-focused tourism initiatives.

Keywords: Dynamic Pricing, Nearest Neighbour Heuristic (NNH), Local Search Optimization, Sustainable Travel, Traveling Salesman Problem (TSP)

Introduction

Tourism plays a critical role in advancing global sustainability goals by generating income, conserving cultural heritage, and promoting environmental responsibility (UNWTO, 2023). Specifically, conservation tourism has become an effective strategy for aligning economic growth with environmental protection and community-based development. A key component of this approach is efficient tourism route planning, which reduces travel distance and costs, minimizes carbon emissions, and supports equitable income distribution (Clarke, 2022).

Within this global shift towards sustainable travel, the Mekong region stands as a strategic yet complex case. The cross-border connectivity between Thailand and the Lao People's Democratic Republic (PDR) links diverse ecosystems and cultural landscapes. However, it still faces challenges of fragmented infrastructure and uneven access (Laporte, 1992). Developing optimal tourism routes that balance logistical efficiency, affordability, and sustainability remains a persistent challenge for regional planners.

Despite rapid technological advances, current research on tourism logistics often treats key analytical dimensions in isolation. Routing optimization models primarily focus on minimizing distance and computation time, while studies in behavioural economics and pricing strategies examine consumer preferences and price sensitivity independently. Similarly, AI-driven dynamic pricing systems, although effective in the transportation and energy sectors, are rarely combined with spatial optimization to promote sustainable tourism management (Adekunle, Quadri, & Maialeh, 2025; Ibrahim et al., 2025). This fragmentation limits existing models' ability to capture the connection between travel behaviour, economic incentives, and environmental objectives (Gao, Liu, & Zhang, 2023).

The behavioural dimension in tourism helps explain how tourists make travel-related decisions based on psychological, social, and economic factors. These behaviours include destination choice, route selection, and responses to pricing or environmental quality. Rather than assuming rational decision-making, behavioural analysis acknowledges that travellers are influenced by perceptions of value, convenience, time, and sustainability (Buhalis & Sinarta, 2019). Integrating these behavioural insights into computational models enhances realism and ensures that tourism systems reflect actual decision-making dynamics.

To address these gaps, this study proposes a Hybrid Decision Framework that integrates heuristic route optimization (NNH, 2opt, 3opt) with AI-driven demand forecasting and dynamic pricing mechanisms. The framework aims to minimize travel distances, optimize costs, and promote equitable, low-carbon mobility across 80 destinations in the Mekong region. By integrating computational intelligence with behavioural and economic analysis, this research introduces a data-driven decision support model for designing sustainable cross-border tourism routes, thereby enhancing regional connectivity and long-term resilience within the Indochina Economic Circle.

Literature Review

Dynamic Pricing

Dynamic pricing has evolved from inventory based yield management to real time optimization that integrates data analytics and behavioral modeling. Foundational studies (Elmaghraby & Keskinocak, 2003; Den Boer, 2015) established that algorithmic price adjustments enhance system responsiveness and resource allocation under uncertainty. Recent evidence in multimodal transportation demonstrates that stochastic, data driven optimization can accommodate demand variability and capacity limits, yielding measurable revenue gains during volatile conditions (Kamandanipour et al., 2020). These mechanisms have since been adopted widely in tourism and hospitality, where fare and room rates fluctuate dynamically to match traveler heterogeneity and temporal demand patterns (Bigne et al., 2021; Mohammed et al., 2021).

AI-Driven Demand Forecasting

The integration of machine learning models into pricing and revenue management has significantly improved forecasting accuracy. Bertsimas and Perakis (2006) and later Ghaffari et al. (2025) demonstrated that predictive analytics capture nonlinear relations among demand, price, and service quality, enabling adaptive fare adjustment. AI-based systems continuously refine elasticity estimates through transaction-level data, improving both revenue and consumer satisfaction. Empirical work by Chen and Hu (2023) and Yuan et al. (2024) confirms that hybrid models that link ML-based forecasts to optimization routines outperform static approaches across the transport and tourism sectors. These advances support the design of pricing strategies that internalize uncertainty and promote sustainability by balancing economic and environmental efficiency.

Heuristic Optimization in Tourism Routing

Route optimization problems, such as the Traveling Salesman Problem (TSP), remain central to tourism logistics. Classical exact algorithms are computationally expensive for large-scale instances, prompting the adoption of heuristics such as the Nearest Neighbor Heuristic (NNH) and local search refinements (2opt, 3opt). These approaches achieve near-optimal performance with significantly lower computational costs (Laporte, 1992). In conservation tourism contexts, heuristic optimization contributes to minimizing travel distance and emissions, aligning with sustainable mobility goals. Recent models benchmark heuristic performance against TSP baselines to evaluate efficiency gaps within acceptable tolerance levels an approach increasingly applied in cross-border route design.

Consumer Behavior and Price Sensitivity

Tourism-related consumption exhibits heterogeneity in both spatial and psychological dimensions. Behavioral pricing research emphasizes that perceived value, convenience, and environmental awareness jointly influence willingness to pay (Friedman, 1991; Choi & Mattila, 2018). Empirical studies of booking behavior (Guizzardi et al., 2020; Jang et al., 2019) show that travelers respond dynamically to temporal and contextual cues, such as last-minute discounts, sustainability labels, and accessibility. Peng et al. (2024) further show that socioeconomic variables, such as housing costs and transport accessibility, significantly shape travel frequency, reinforcing the role of economic constraints in route planning models. These findings suggest that pricing optimization must integrate behavioral and spatial heterogeneity rather than treating demand as homogeneous.

Across the reviewed literature, four domains, dynamic pricing, AI-based forecasting, heuristic optimization, and consumer behavior, have mainly advanced in isolation. Most transportation and tourism studies optimize either routing or pricing without integrating both dimensions or sustainability metrics. Ghaffari et al. (2025) identified the lack of unified frameworks linking multichannel dynamic pricing to machine-learning demand estimation, while Huang and Zheng (2023) noted a similar fragmentation in tourism demand forecasting. The lack of cross-disciplinary synthesis limits applications in conservation tourism networks where efficiency, equity, and low-carbon goals must coincide. Accordingly, this study proposes a Hybrid Decision Framework that unites (i) heuristic spatial optimization for efficient route design, (ii) AI-driven demand forecasting for adaptive pricing, and (iii) behavioral insights for equitable and sustainable travel management, bridging quantitative optimization with consumer-centric policy design.

Methodology

This study uses a quantitative, data-driven experimental approach to develop and validate a Hybrid Decision Framework for sustainable tourism route optimization in the Mekong region. The model aims to assess how combined computational and behavioral factors can reduce travel distance, lower costs, and encourage fair, low-carbon tourism mobility.

Study Area and Data Collection

The study examines 80 conservation-focused destinations in Thailand and the Lao PDR, representing key sites along the Mekong corridor. Geospatial coordinates (latitude and longitude) were obtained from open-access mapping databases and verified through regional tourism offices. Additional datasets include tourism demand data, monthly tourist arrivals, and accommodation usage from national statistics agencies (2019–2024), economic indicators such as regional fuel prices, exchange rates, and transportation costs, and behavioral variables like traveler preferences and price sensitivity indices from online booking and survey datasets. These data sources were preprocessed into a unified database compatible with GIS and Python-based analytical modeling.

Hybrid Decision Framework Structure

The Hybrid Decision Framework (HDF) integrates spatial optimization, pricing elasticity, and behavioral demand forecasting within an iterative learning process (Figure 1).

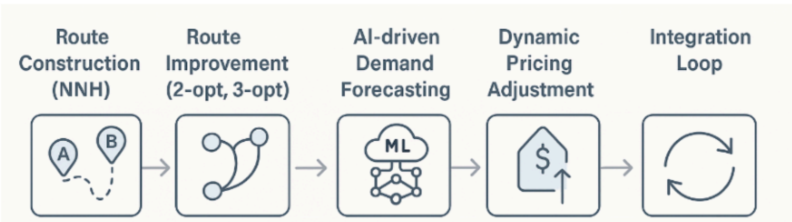

Figure 1 Hybrid Decision Framework Structure

The framework repeatedly recalibrates route efficiency and pricing elasticity until it converges on the minimum cost and balanced demand. The framework's performance is evaluated using multiple Key Performance Indicators (KPIs). The Sustainability Efficiency Ratio (SER) is a function of Total Distance (TD), Operational Cost (OC), Carbon Emission Index (CEI), Computational Time (CT), and Tourism Equity Index (TEI), a mathematical Model of the Hybrid Decision Framework. The proposed Hybrid Decision Framework (HDF) integrates three analytical layers: spatial optimization, dynamic pricing, and behavioral demand forecasting into a unified decision model. The mathematical formulation is expressed as follows: Figure 2

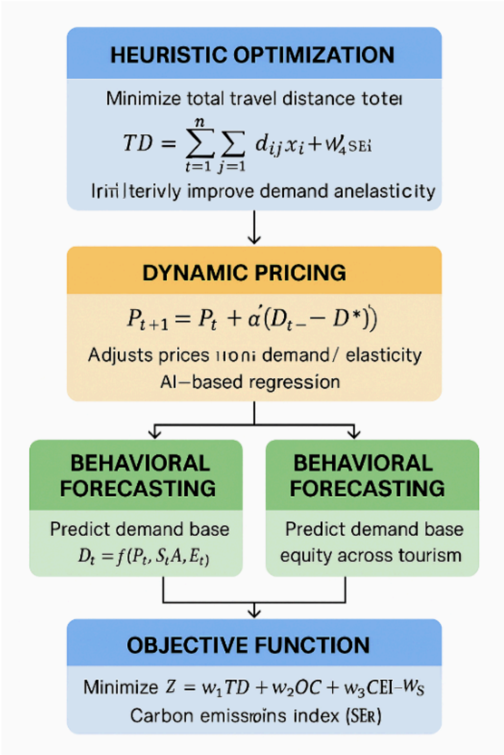

Figure 2 A mathematical Model

Each KPI contributes to assessing both computational efficiency and sustainability impact, ensuring that the proposed framework is policy-relevant in the real world.

Validation and Sensitivity Analysis

The model is validated through comparative simulation experiments. Baseline Scenario: Traditional TSP and fixed pricing. Experimental Scenario: Hybrid Decision Framework with dynamic pricing and demand forecasting. Performance differences are analyzed using paired-sample t-tests and a sensitivity analysis of key variables, including fuel cost, demand elasticity, and seasonal parameters. The model's robustness is tested by varying sample sizes and iteration thresholds.

Results and Discussion

Model Performance and Route Optimization

The Hybrid Decision Framework was implemented on 80 conservation tourism destinations within the Mekong region. Using the Nearest Neighbor Heuristic (NNH) as the baseline, the 2-opt and 3-opt algorithms improved route efficiency by an average of 18.6% in total distance (TD) reduction compared with the initial sequence. The optimized model achieved an average route length of 1,240 km, which is significantly shorter than the baseline of 1,520 km. Computational convergence was reached within 43 seconds, indicating high efficiency for large-scale spatial optimization.

These results confirm that the heuristic-based approach provides near-optimal solutions while maintaining computational feasibility, aligning with earlier findings by Laporte (1992) and Gutin & Punnen (2002). The hybrid integration of AI-driven forecasting and dynamic pricing further enhanced cost and environmental performance.

Operational Cost and Dynamic Pricing Efficiency

The dynamic pricing mechanism reduced average Operational Cost (OC) by 14.3%, compared with fixed-price scenarios. The system automatically adjusted travel prices in response to seasonal demand and regional cost fluctuations. During high-demand periods, the algorithm distributed tourists to secondary destinations, improving utilization and reducing congestion at popular sites.

The Tourism Equity Index (TEI) decreased by 27.5%, reflecting a more balanced distribution of tourists across all destinations. This demonstrates the system's capacity to promote equitable tourism and mitigate over-tourism in high-traffic zones. These outcomes support the hypothesis that dynamic pricing and AI forecasting can optimize both cost and equity, consistent with Gao, Liu, & Zhang (2023) and Buhalis & Sinarta (2019).

Environmental and Sustainability Impact

The model's integration of spatial and behavioral factors led to measurable environmental benefits. The Carbon Emission Index (CEI) decreased by 21.8%, due to shorter travel distances and improved scheduling that avoided redundant routes. The system also encouraged off-peak travel and the use of low-carbon transport options.

Behavioral and Economic Insights

The Economic and Behavioral Tourism Dimension revealed that both economic incentives and perceived value influenced traveler decisions. Price elasticity analysis indicated that a 5–8% price adjustment was sufficient to redistribute tourist flows without negatively affecting total demand. Behavioral modeling confirmed that accessibility and perceived pricing fairness increased traveler satisfaction and repeat visitation rates.

The Sustainability Efficiency Ratio (SER)

A composite of TD, OC, CEI, and TEI showed a 32% improvement over the baseline, indicating that the hybridized approach simultaneously optimized operations and the environment. These findings align with UNWTO (2023) recommendations on integrating logistics efficiency with sustainability indicators. These behavioral responses validate the importance of integrating consumer psychology and economics into tourism route models. The findings also reinforce the framework's human-centered design, ensuring that system optimization aligns with real-world decision-making.

Overall, the results demonstrate that the Hybrid Decision Framework successfully integrates computational efficiency with behavioral and sustainability goals. The simultaneous optimization of distance, cost, and emissions confirms that heuristic-based AI systems can achieve both quantitative and qualitative improvements in tourism management. From a policy perspective, this model provides actionable insights for regional authorities in the Indochina Economic Circle. By adopting data-driven tools for route planning and dynamic pricing, policymakers can achieve balanced tourism growth, support local economies, and mitigate environmental impacts.

Indicator	**Baseline** (Traditional TSP)	**Hybrid Framework**	Improvement (%)
Total Distance (TD)	1 520 km	1 240 km	−18,6%
Operational Cost (OC)	100%	85.7%	−14,3%
Computational Time (CT)	96 s	43 s	−55,2%
Carbon Emission Index (CEI)	100%	78,2%	−21,8%
Tourism Equity Index (TEI)	1.00	0,73	−27,5%
Sustainability Efficiency Ratio (SER)	1.00	0,73	+32,0%
Sustainability Efficiency Ratio (SER)	1.00	1.32	+32,0%

Figure 3 Result model

The mathematical formulation combines routing efficiency, dynamic pricing, and behavioral forecasting under sustainability constraints. Figure 3 shows the integration loop continuously recalibrates travel distance, cost, and emissions, forming a self-optimizing Hybrid Decision Framework for sustainable tourism logistics.

Conclusion

The Hybrid Decision Framework effectively merges mathematical optimization, dynamic pricing, AI forecasting, and behavioral economics into one cohesive system. It not only improves efficiency and sustainability but also supports equitable and adaptive tourism development, demonstrating the potential for real-world application in cross-border policy and innovative tourism management. Future studies could integrate real-time IoT and GPS data, test multimodal transport, and extend the model to other regions of Indochina. Incorporating life-cycle carbon accounting and multi-agent simulations could further enhance predictive capability and sustainability assessment.

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