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Optimizing Service Scheduling by Genetic Algorithm Support Decision-Making in Smart Tourism Destinations

Pannee Suanpang[1,*], Pitchaya Jamjuntr[2]

1 Department of Information Technology, Faculty of Science & Technology, Suan Dusit University, Bangkok, Thailand., pannee_sua@dusit.ac.th
2 Department of Electrical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangkok, Thailand., pitchaya.jam@kmutt.ac.th.

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ABSTRACT

Smart tourism destinations are characterised by the integration of advanced technologies and devices to ensure visitors enjoy a seamless and environmentally responsible experience. A key challenge for such destinations lies in efficiently managing and delivering services to meet tourists' expectations while upholding sustainability principles and resource management practices. This study aimed to explore the application of genetic algorithms (GAs) in optimising service scheduling, thereby supporting decision-making processes and enhancing tourism destination services. The research employed a service scheduling methodology that directed the algorithm towards maximising efficiency and customer satisfaction, in contrast to traditional organisational scheduling methods. The methodology centred on the implementation of an algorithmic approach in service delivery management, prioritising operational efficiency and improved customer experience over conventional scheduling techniques. Data collected were systematically analysed, resulting in the development of a theoretical framework based on the findings. The results demonstrated that genetic algorithms significantly enhance service scheduling efficiency when used alongside other methods. The findings underscore the pivotal role of GAs in enabling businesses to achieve time and cost savings while improving customer satisfaction. Furthermore, the study highlights GAs' capacity for adaptability, allowing schedules to be adjusted rapidly in response to changing circumstances, thus providing flexibility and responsiveness to variations in demand. Finally, the research identifies opportunities for innovation and diversification in applying GAs for time scheduling within the tourism sector. It also emphasises the importance of integrating real-time information into scheduling systems to improve service provision at tourist sites. This approach not only enhances the competitiveness of tourism destinations but also adds substantial value to the industry by enriching tourists' experiences and fostering sustainable practices

1. Introduction

* *Corresponding author.*
E-mail address: pannee_sua@dusit.ac.th

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The global economy significantly benefits from tourism services, which are major contributors to Gross Domestic Product (GDP) and employment across various countries [1-2]. The tourism sector encompasses a wide range of services, including accommodation, transportation, dining, entertainment, and excursions, all of which are integral to the industry and play a crucial role in influencing tourists' satisfaction and loyalty to destinations [1-3]. Among these components, the accommodation sector is particularly pivotal, as lodging options—ranging from hotels and luxury resorts to vacation rentals—significantly shape visitors' perceptions of a destination, as illustrated in Figure 1 [4]. Tourists often evaluate accommodation based on factors such as cleanliness, staff friendliness, and overall comfort standards, and positive experiences in these areas can encourage repeat visits and foster positive word-of-mouth, ultimately driving destination growth and development [5-6].

Fig. 1. Tourism Services

The provision of transportation services plays a crucial role in shaping tourists' overall experiences. Accessible and convenient modes of transport, such as airlines, trains, buses, and car rental services, enhance tourists' ability to navigate destinations and access attractions with ease [7]. Moreover, transportation services are essential for connecting locations within a region, thereby promoting the concept of stopover tourism and encouraging exploration beyond primary attractions [8]. Culinary experiences also hold significant importance, as tourists often seek opportunities to sample local dishes and enjoy unique dining experiences [9]. Restaurants, street food vendors, and culinary tours immerse visitors in the cultural fabric of a destination, offering them a deeper connection to the local gastronomy [10]. Memorable dining experiences not only contribute to tourists' satisfaction but also create lasting impressions, potentially inspiring future visits and fostering loyalty to the destination [11].

Tourism services are intrinsically connected to environmental sustainability and responsible tourism practices. Eco-friendly accommodations and responsible tour operators play a vital role in supporting environmental conservation and promoting community development, aligning with sustainable tourism objectives [12]. With tourists increasingly aware of the environmental impact of their travel choices, there is a growing preference for destinations and services that adhere to sustainable practices [13]. Tourism services encompass a wide range of offerings, including accommodation, transportation, dining, and sustainability initiatives, all of which significantly influence tourists' experiences and their choice of destinations. These components are critical in enhancing tourist satisfaction and fostering destination loyalty. As the tourism industry continues to evolve, prioritising the improvement and integration of these services is essential for advancing Sustainable Development Goals (SDGs).

As the early stages of artificial intelligence (AI) are embraced, emerging technologies are increasingly reshaping the business landscape, particularly within the tourism industry, where services are generated, marketed, and managed [14-16]. Globally, tourism has contributed significantly to economic value, fostered cultural exchange through travel and social interactions, and advanced sustainable development goals [17]. However, the industry's growth trajectory also presents numerous challenges that stakeholders must address to enhance efficiency and competitiveness in an ever-changing environment [17-19]. To tackle these challenges, researchers have adopted innovative approaches, including the application of GAs, which are particularly effective in solving complex problems within the tourism sector [20-21]. One notable issue is the scheduling of staff providing tourism services, a problem widely recognized among combinatorial optimization challenges and production management concerns. The complexity of these scheduling challenges lies in evaluating all potential schedules; as the scope of the problem grows, so does the difficulty, due to the exponential increase in the number of possible scheduling combinations [22].

1.1 Problem Statement

The application of GAs in tourism faces challenges due to the complexity of the optimization process. GAs operate through selection, crossover, and mutation, transforming potential solutions into optimal outcomes, but these operations can be computationally intensive and time-consuming. This poses difficulties in real-time decision-making within the dynamic tourism industry. Additionally, the efficiency and reliability of GAs depend heavily on the quality and representation of the problem space [23-24]. The efficiency and effectiveness of GAs are significantly influenced by the design of fitness functions, garbling schemes, and parameter settings. Developing a clear understanding of the problem space and fine-tuning algorithmic parameters are critical yet challenging tasks. Moreover, the application of GAs in tourism raises ethical considerations. For example, GAs could be utilised to create pricing strategies that risk price discrimination or unfair practices, potentially disadvantaging certain customer groups. Ensuring equity and transparency in GA-driven processes is essential to maintaining trust and integrity, particularly in route scheduling and decision-making for tourism planning [13-25].

GAs are heuristic search methods modelled on natural selection, widely applied in fields such as finance and engineering; however, their application in the tourism sector remains underexplored [38]. This research offers significant value by examining the economic, social, and environmental benefits of optimizing service scheduling for various stakeholders in the tourism industry [26]. Enhancing service scheduling can lead to cost savings through efficient resource allocation and reduced staff turnover. Additionally, minimizing wait times and improving customer experiences can boost satisfaction and loyalty, ultimately driving profitability and enhancing the overall tourism experience. From a social perspective, efficient service scheduling can significantly enhance the tourist experience by reducing stress and increasing overall satisfaction, which is especially critical for destinations heavily reliant on tourism. The quality of the tourist experience plays a vital role in shaping a destination's reputation [24][27]. From an environmental standpoint, optimized service scheduling can lower energy consumption and carbon emissions, particularly in areas with high tourist footfall. By minimizing waiting times and streamlining service operations, businesses can alleviate congestion and reduce the environmental impact of tourism activities.

1.2 Research Question

1) What are the key challenges faced by smart tourism destinations in optimising service scheduling?
2) In what ways can GAs be employed to enhance service scheduling in smart tourism destinations?
3) Are GAs more effective in optimising service scheduling compared to traditional scheduling methods?
4) What are the primary advantages of employing GAs for service scheduling in smart tourism destinations?
5) How can GAs adapt to dynamic conditions and reoptimize schedules in real time?
6) What are the potential applications of GAs in optimising service scheduling within the tourism sector?

1.3 Objective and Contribution

The aim of this study was to expand knowledge on the adaptation and application of GAs in the tourism sector, particularly within smart tourism destinations, to provide recommendations that could support business decision-making and enhance the customer experience. This research contributes to a deeper understanding of how GAs can improve business strategies and customer satisfaction in tourism. It highlights the potential of GAs to optimise service scheduling in tourism operations, offering valuable insights for future research. The study suggests that incorporating real-time data into scheduling processes could enhance efficiency and effectiveness, benefiting both businesses and travellers.

2. Literature Review

2.1 Genetics Algorithms (GAs)

GAs are a class of optimisation methods inspired by the principles of selection and genetics observed in nature's processes of evolution and adaptation. They are particularly effective in solving complex optimisation problems, such as task scheduling and resource allocation. Researchers have made significant strides in enhancing both the theoretical foundations and practical applications of GAs. A key advantage of GAs is their ability to adapt and respond to changing conditions and constraints that emerge during the optimisation process. Rooted in evolutionary algorithms, GAs replicate the process of natural selection, making them particularly useful when traditional optimisation methods fail or when exploring under-researched areas, as illustrated in Figure 2 [27].

The key stages in running GAs involve initializing the process, evaluating the fitness of individuals, selecting candidates for reproduction, and determining which individuals will form the next generation through replacement [28]. The replacement stage is particularly important, as it decides which individuals, from both the population and the offspring, will be retained in the new generation, ensuring a consistent population size while favouring the survival of the fittest individuals [26][29]. This cycle of selection, reproduction, and replacement continues until a termination criterion is met. The stopping criteria may include a limit on the number of iterations, the achievement of a specific fitness goal, or reaching a predefined threshold of improvement, at which point the algorithm halts and the most optimal solution at that stage is considered final [28-29].

Numerous studies have examined the application of GAs in various fields. For instance, Cao [17] introduced an objective genetic algorithm to address dynamic job scheduling problems, demonstrating that their approach outperformed traditional scheduling methods in terms of both effectiveness and flexibility. GAs are particularly effective for solving complex search spaces, as demonstrated by Mahdi and Esztergár-Kiss [30], which proposed using a GA to address a multi-objective vehicle routing problem with time constraints, highlighting its superiority over other optimization methods. GAs have been widely applied across domains such as engineering, optimization, and machine learning, where they excel at navigating challenging problem scenarios and exploring solution spaces that are difficult for conventional methods to handle [31]. Furthermore, GAs have gained increasing attention in recent years due to their ability to resolve complex optimization issues. Researchers have made significant progress in enhancing the understanding and application of GAs by improving their flexibility and scalability, and by integrating them with other optimization techniques to create hybrid approaches.

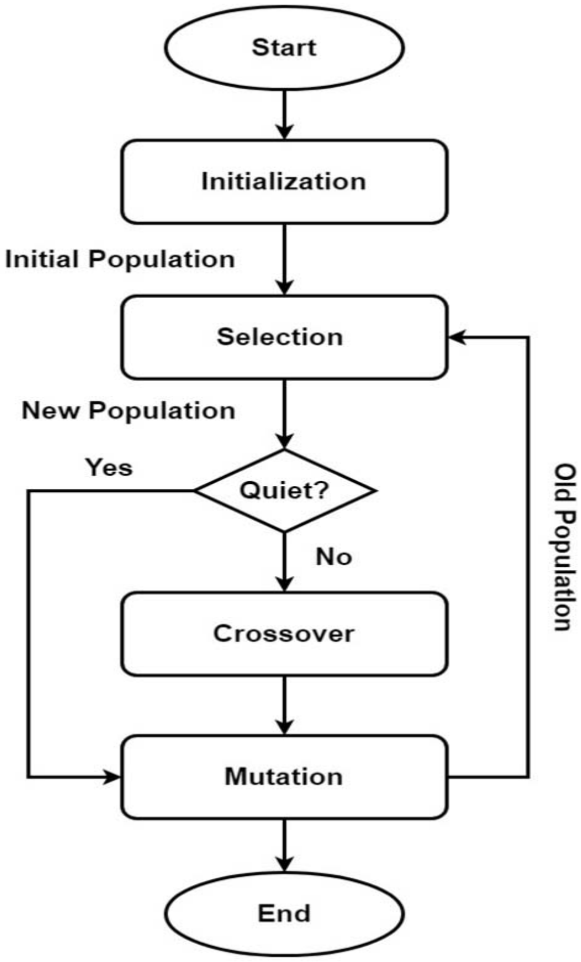

Fig.2. The steps of the Gas

2.2 Traditional Algorithms

Traditional scheduling methods, such as manual and rule-based approaches, have been widely used in the tourism industry but are limited in effectiveness, precision, and scalability. Manual scheduling, for instance, can be time-consuming and error-prone, often leading to reduced productivity, as noted by [32]. They recommended automated scheduling software to improve productivity and accuracy. As a result, GAs have emerged as a more efficient alternative. GAs, inspired by natural selection and genetics, offer advantages in solving optimization problems where traditional methods fall short. Tu et al. [33] demonstrated the effectiveness of GAs in optimizing tour bus scheduling, showing that it outperformed conventional techniques in terms of quality, efficiency, and adaptability.

2.3 Smart Tourism Destinations

STDs are destinations that integrate information and communication technologies (ICTs) such as the Internet of Things (IoT), big data analytics, AI, and mobile applications to enhance tourism experiences. These technologies improve various aspects of tourism, including attractions, accessibility, amenities, packages, activities, and services, aiming to boost both visitor satisfaction and the destination's competitiveness [34]. The concept of STDs has transformed how tourists interact with technology and data-driven strategies in the tourism industry. A key objective of STDs is to offer personalised experiences for travellers through AI-powered technologies. By analysing data, AI systems help destinations understand visitor preferences, while mobile applications provide real-time information on tourist spots, accommodation, and activities tailored to individual interests [35].

Destination managers benefit from technologies that provide real-time data and insights for effective decision-making. Data analytics helps manage tourist movements, crowd control, traffic, and environmental impact [27][36]. Smart technologies optimize resource allocation, reduce energy use, and minimize environmental harm. While there is substantial international research on STDs [16][37], studies have specifically explored the role of customized services in enhancing tourism experiences [34][38], conceptual frameworks for studying STDs [36], and their strategic impact on destination management [12][37]. A key element of STDs is the integration of digital infrastructure, where ICTs play a crucial role in enhancing the tourist experience [37]. Tourists now rely on high-quality internet and mobile networks for instant access to information, aiding in decisions about accommodation, attractions, and activities [11] [39-40]. Smart accommodations further enhance guest experiences with features like keyless entry, smart thermostats, and in-room automation systems, which also contribute to energy savings and sustainability in tourism [19][41].

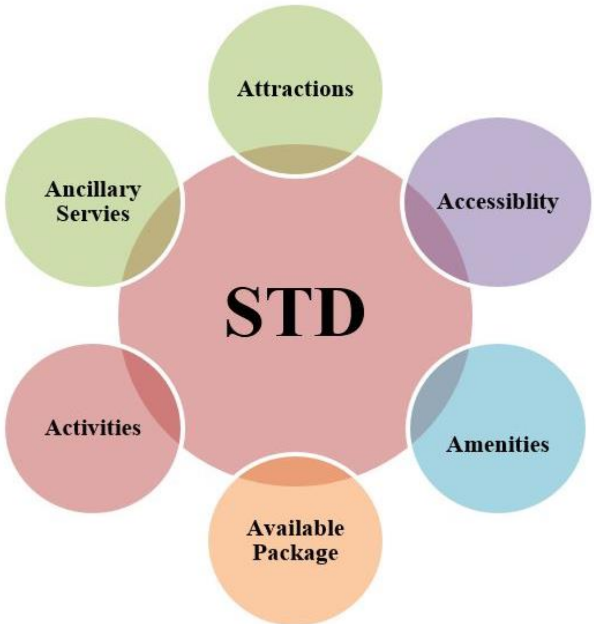

Fig. 3. 6A of Smart Tourism Destination Components

Community engagement is a fundamental component of STD initiatives. The cultural integration of local communities and their involvement in decision-making processes fosters the sustainability of tourism development [23]. Residents, as key stakeholders, contribute to the authenticity and preservation of the destination's cultural heritage [40]. However, the anticipated benefits of STDs are not without challenges. The implementation of such systems is often accompanied by concerns related to privacy, data protection, and the digital divide, which destinations must address 37]. Moreover, the adoption of various technologies necessitates significant investment in both infrastructure and human resource development.

2.4 Optimizing Services Scheduling

Optimising service scheduling is essential across various sectors to ensure effective resource utilisation, enhance customer satisfaction, and improve operational efficiency. The key components of schedule optimisation (Figure 4) include rules, historical data, business objectives, customer needs, weather conditions, and personal factors [36]. Numerous studies have highlighted the significance of advanced algorithms in optimising service schedules. Metaheuristic algorithms, such as genetic algorithms, simulated annealing, and particle swarm optimisation, have been applied in industries like healthcare, transportation, and customer service to address complex scheduling challenges [38]. These algorithms are effective in generating optimal or near-optimal schedules while accommodating diverse constraints and preferences. The advent of real-time data has transformed service scheduling. Real-time scheduling systems allow businesses to quickly adapt to fluctuating demands and disruptions. IoT devices generate continuous data streams that can be analyzed to optimize schedules in real time, ensuring efficient resource allocation and timely service delivery [41].

Fig. 4. Schedule Optimization [38]

Personalization in service scheduling has attracted significant scholarly attention. By incorporating customer preferences, businesses can offer customized services that enhance customer satisfaction and foster loyalty. Machine learning algorithms analyse historical data to predict customer preferences and behaviours, enabling businesses to optimise schedules in a manner that centres on the customer [49]. Despite advancements in optimisation techniques, challenges remain. Complex constraints, diverse service requirements, and the need to balance cost-effectiveness with customer satisfaction continue to present difficulties [39]. Furthermore, ethical considerations regarding privacy and fairness in scheduling decisions must be carefully addressed when designing and implementing scheduling algorithms.

2.5 GAs Implications for Smart Tourism Destinations

GAs are commonly used in tourism research to optimise service scheduling and resource allocation. For example, Li and Zhang [42] applied a GA to optimise flight schedules based on factors like revenue, cost, and passenger demand. Other approaches, such as tournament selection, are used to optimise hotel room pricing [43]. However, challenges like data privacy, computational complexity, and real-time decision-making must be addressed for successful GA implementation in smart city tourism. Studies have also explored GAs for route optimisation, travel mode recommendations, and dynamic resource allocation in smart tourism cities, highlighting their potential to improve tourist experiences and mobility [30][32][44]. Additionally, hybrid GAs combining simulated annealing and gradient search methods have proven effective in optimising tourism service problems and ensuring sustainability in smart city tourism destinations.

3. Materials and Methods

3.1 Smart Tourism Destination (STD)

This study focused on Rayong, a smart city on Thailand's eastern seaboard, currently undergoing industrial growth and urban expansion. The concept of Rayong as a smart tourism destination aims to leverage technology, innovation, and data to address urban challenges, enhance residents' quality of life, foster economic development, and promote sustainable solutions [45]. Figure 5 illustrates the smart cities of Rayong within the research areas. Despite the challenges posed by the COVID-19 pandemic, efforts were made to conceptualise an STD prototype for implementation in Rayong province [20][36]. In this Thai case study, tourists interacted with the system by seeking travel information, planning their journeys via applications and social networks, making reservations through online platforms, and conducting online check-ins through smart hotel systems. They also experienced tourism using GIS, AR, and QR codes at various attractions, and shared their feedback and intentions of revisiting via social media. While several initiatives have been launched within the Rayong smart tourism destination (Figure 5), further evaluation is needed to assess their impact on the overall tourism experience, particularly from the perspective of international tourists.

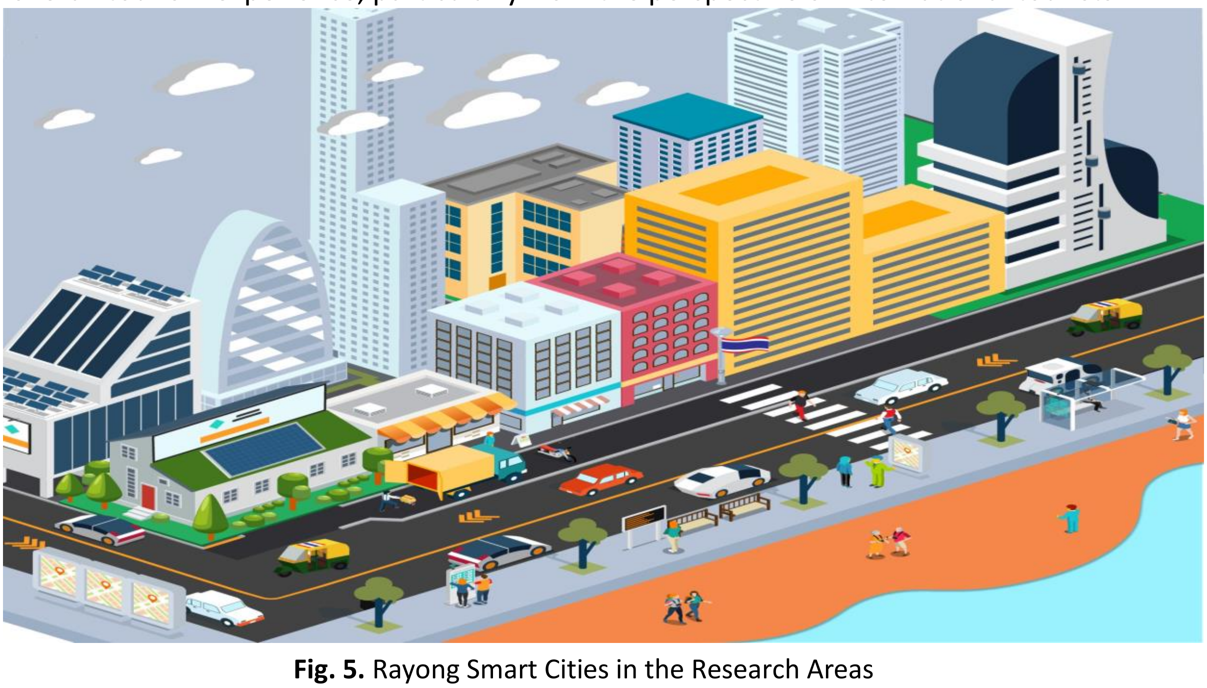

Fig. 5. Rayong Smart Cities in the Research Areas

3.2 Research Framework

The research framework for this study is shown in Figure 6.

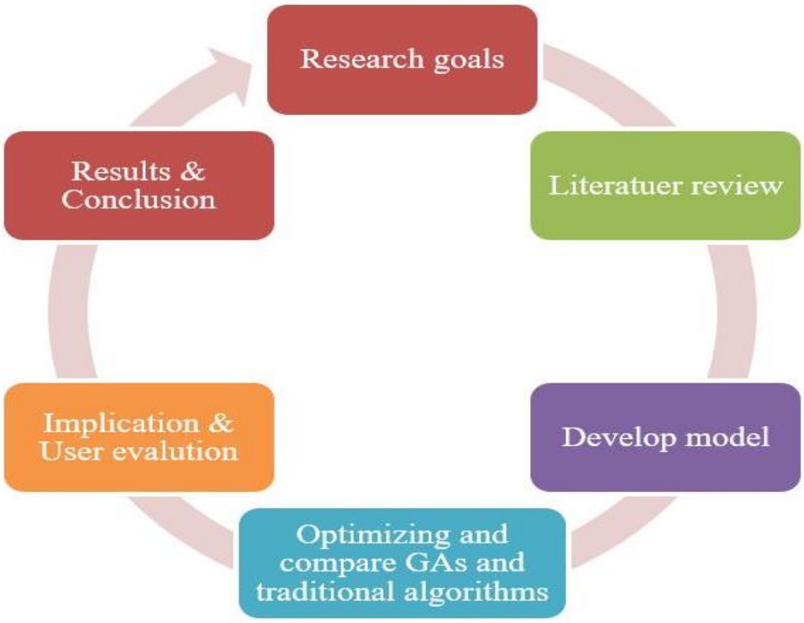

Fig. 6. Research Framework

1. Research Goals: To explore the application of GAs in the tourism sector and develop a model demonstrating their benefits for business process improvements and user satisfaction.
2. Literature Review: A review of existing literature on the use of GAs in tourism, providing insights into the current state of research and highlighting areas requiring further investigation.
3. Theoretical Model: A comprehensive model explaining GAs, their multi-variate relationships, and other key variables, aimed at studying the impact of GAs on various tourism sectors.
4. Methodology: A detailed description of the study design, including data collection and analysis methods, to compare the performance of GAs with traditional algorithms in different tourism scenarios.
5. Implications: Identifying high-performing tourism algorithms for integrating scheduling into tourism services, including an evaluation of user feedback on tourism scheduling services.
6. Results: Presenting current findings regarding the application of GAs in promoting tourism sustainability.
7. Conclusion: Drawing conclusions based on the arguments and findings, focusing on the use of GAs in the tourism industry.

3.3 Research Design

The methodology employed in this study is based on GAs, chosen for their efficiency in searching for optimal solutions. GAs are particularly adept at handling nonlinear relationships between variables and can identify globally optimal solutions. The process of implementing GAs for service scheduling in the tourism industry is outlined in Figure 7. In this study, GAs were employed to optimise service scheduling in the tourism industry. The data were collected from a comprehensive database of service providers, which is crucial for applying GAs to enhance service scheduling. The use of GAs is justified by their proven ability to navigate complex problem spaces and identify optimal solutions, particularly in managing nonlinear relationships between variables. The database, which contains detailed information on service providers, including their locations, service types, and availability, was compiled through a partnership with a tourism industry association. Data collection was conducted over a six-month period to ensure the dataset was both comprehensive and representative. This database plays a key role in both the analysis and the implementation of GAs, ensuring efficient and effective service scheduling solutions in the tourism industry.

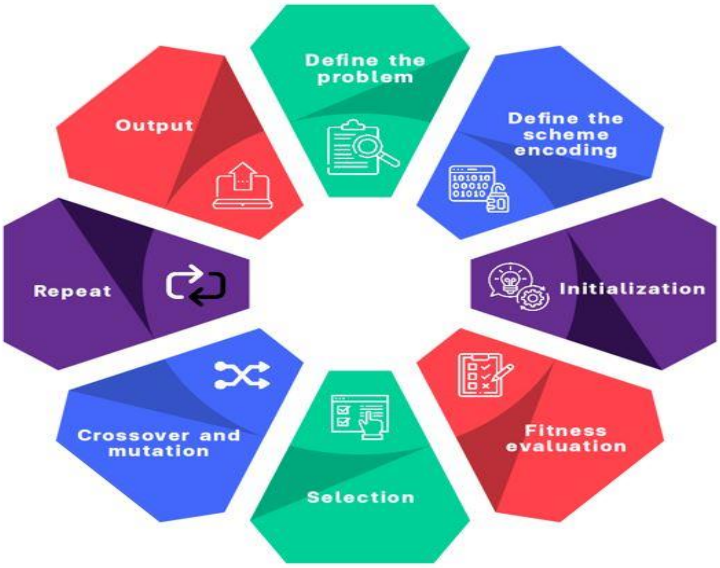

Fig. 7. Steps Involved in Implementing the Genetic Algorithms

The database used in this study plays a crucial role in implementing GAs to optimize service scheduling in the tourism industry. The selection of GAs as the methodology is based on their ability to efficiently navigate complex problem spaces and identify optimal solutions. GAs are particularly well-suited for handling nonlinear relationships between variables, which enhances their capacity to find globally optimal solutions. The database provides detailed information on service providers, including their location, type of service, and availability. This data was obtained through collaboration with a tourism industry association. Data collection for this research took place over a six-month period, beginning in June 2023. This duration was intentionally chosen to ensure a representative sample of service providers and their activities within the tourism industry. The six-month period allowed for the capture of patterns and fluctuations in service provision, facilitating a more thorough analysis and interpretation of the data collected.

Specific criteria were applied in selecting the data used in this case study. Service providers included in the study were those offering particular services, such as hotel rooms and tour packages, and operating within defined geographical areas. Only providers with a minimum level of activity during the study period were included. The data collection process went beyond merely gathering raw data; it also involved verification to ensure that the statistics were accurate and comprehensive. Missing or inconsistent data were addressed through further investigation or direct contact with the service providers. The data collection process was designed to ensure that the data used in the study was not only relevant and reliable but also representative of the service providers within the tourism sector under investigation.

3.4 Data Processing

3.4.1 Data Source and Collecting

Data Source

Quantitative data were collected from the following sources:

1) Databases from smart tourism destinations and official tourism websites of the Tourism

Authority of Thailand in Rayong province, which track monthly and yearly tourist statistics.
2) Business reports from tourism-related companies, such as hotels, restaurants, and transportation services.
3) Survey Participants: The study population includes tourists visiting Rayong province, tourism business operators, and government agencies involved in tourism management. A purposive sample of 130 users of the GAs system who travelled to Rayong was selected. This sample size is deemed sufficient for data saturation and providing comprehensive insights into the research questions, ensuring participants had direct experience with the GAs system and its role in service scheduling.

Qualitative data were collected from interviews with 64 tourists in Rayong province. The data collection process was approved by the Ethical Committee. The interviews addressed eight key issues (detailed in the dataset files):

1) Respondents' Demographics and Background: Collecting demographic data to understand the profile of visitors and their choice of destination.
2) Travel Preferences and Experience: Exploring how tourists plan their trips, when they schedule activities, and the factors influencing their choices.
3) Service Provision and Scheduling Experience: Assessing tourist satisfaction and challenges regarding service scheduling.
4) Smart Instruments in Travel: Gauging knowledge and use of smart tourism technologies and their implementation during trips.
5) Artificial and Genetic Algorithms in Service Planning: Evaluating tourists' comfort and receptiveness to using optimization methods, such as GAs, for service scheduling.
6) Customer Satisfaction and Preferences: Identifying key factors and rankings of customer satisfaction in relation to service delivery schedules and prioritization of services.
7) Resource Use Efficiency and Sustainability: Understanding tourists' views on the effectiveness of resource use and the need for sustainable practices at tourism destinations.
8) Overall Evaluation and Suggestions: Gathering general impressions and recommendations for improving service scheduling and related travel experiences.

Data Collecting

In this study, data was collected through interviews with tourists as respondents (Figure 5). This data gathering procedure was systematic to ensure credibility and accuracy. Below is a text box providing more detailed information on the data collection and analysis phases.

Fig. 8. Data Collection from the Questionnaire and Interview with the User of the GAs System

3.5 Steps of Data Collection

Preparation: Prior to the interviews, an interview guide was developed to ensure consistency across all interviews. The guide included questions designed to explore the tourists' habits, past experiences, and their approach to service scheduling in STDs.

Respondent Selection: A diverse sample of tourists was chosen, representing various age groups, nationalities, and travel purposes.

Pilot Testing: The interview guide was pre-tested with a small group of tourists to identify potential issues in the question structure or other aspects of the guide. Adjustments were made based on the feedback received.

Interview Scheduling: Interviews were arranged at convenient times and locations for the tourists, ensuring minimal disturbances and interruptions.

3.6 Qualitative Data Collection

Close-Ended Questions: The research paper utilized close-ended questions to gather tourists' behaviours and opinions on related issues, allowing for the collection of a broad range of qualitative data.

Follow-Ups: Interviewers employed probing follow-up questions to explore selected responses in greater depth, leading to a more comprehensive understanding of tourists' views.

Observation Notes: In addition to interview responses, researchers documented participants' non-verbal communication, intonation patterns, and other behavioural cues to enrich the data.

3.7 Data Extraction

Beyond provider names, the extracted data from the databases includes several key pieces of information vital for the study:

Location Information: This includes details about the geographical locations of each service provider, which help in analysing the distribution of services across Rayong. By identifying the exact coordinates or addresses of accommodations, attractions, and amenities, we can assess the regional clustering of services within the destination.

Service Types: The categorization of service providers based on the services they offer enables targeted optimization strategies. For example, differentiating between accommodation providers (e.g., hotels, resorts) and experiential services (e.g., tour packages, guided excursions) allows for the development of specialized scheduling algorithms for each category. This approach ensures that the diverse preferences and interests of tourists visiting Rayong are effectively addressed, facilitating better service organization and analysis.

By categorizing service providers into distinct categories, we can streamline data analysis, develop targeted optimization strategies, and improve service scheduling efficiency within Rayong's smart tourism destination. This categorization helps identify trends, patterns, and opportunities specific to each service type, allowing stakeholders to optimize resource allocation and enhance the overall tourist experience effectively.

Availability Metrics: Quantitative data on service availability provides insights into the flow of service provision over time, including occupancy rates for lodging and available tour slots for guided experiences. This analysis helps identify high-demand periods, allowing for the optimization of resource distribution and effective management of scheduling conflicts. By leveraging this data, we can develop adaptive scheduling algorithms that respond to changing demand levels, enhancing service delivery and customer satisfaction throughout the year.

Temporal Information: Analyzing time stamps that show when services are available or used offers valuable insights into patterns and trends in the tourism destination. By examining time-related details such as accommodation check-in/check-out times or tour departure schedules, we can identify peak hours and optimal timeframes for service provision. This time analysis informs scheduling improvements, helping maximize resource utilization and minimize visitor wait times.

Additional Relevant Parameters: Depending on the database structure and available data, further analysis can be enhanced by including additional details such as customer reviews, pricing information, and specific service characteristics like amenities or tour inclusions. Incorporating these factors allows for a deeper understanding of service quality, pricing trends, and customer preferences, enabling the refinement of optimization strategies, improved pricing tactics, and tailored service offerings to meet tourists' expectations.

By considering these criteria and extracting relevant data, the study ensures the dataset is suitable for applying GAs to optimize service scheduling in tourism. The data was validated for accuracy and completeness, with any inconsistencies addressed through further research or direct contact with service providers. This process ensured the data's relevance, reliability, and representation of the tourism industry.

3.8 Data Analysis

The data processing and analysis phases were carried out using Python, a versatile programming language that incorporates widely used libraries such as Pandas, NumPy, and Matplotlib. The specific versions of the key software utilised were Python 3.8, Pandas 1.2.1, NumPy 1.19.2, and Matplotlib 3.3.2. Python 3 was chosen for its flexibility and the broad selection of libraries available, which are particularly well-suited for dataset analysis.

Programming Language: Python 3.8 was selected as the programming language due to its general-purpose nature and its extensive array of libraries that are well-suited for managing data analysis tasks.

Libraries: The study primarily utilised Pandas (1.2.1), NumPy (1.19.2), and Matplotlib (3.3.2). Specifically, Pandas was employed for data cleaning and manipulation, NumPy for statistical computing, and Matplotlib for generating graphs and charts.

These tools enabled efficient visualisation of the collected data. Custom scripts were developed to implement the GA methodology for optimising service scheduling. The scripts were specifically designed to meet the unique requirements and objectives of the study, taking advantage of Python's flexibility and ease of implementation. The code is publicly available for access and citation, and a project registration has been created to ensure future availability and facilitate citation through the assignment of a Digital Object Identifier (DOI). The analysis code is distributed under the MIT License, an OSI-approved license, allowing users to freely use and distribute the code with appropriate attribution.

The primary parameters used in the GAs were the population size, mutation rate, and crossover rate. The population size refers to the maximum number of candidate solutions evaluated in each iteration of the algorithm. A larger population size increases solution diversity but also lengthens the algorithm's execution time. The mutation rate determines the likelihood of a solution undergoing mutation, assuming a genotypic structure for each population member. A higher mutation rate allows for a broader exploration of the solution space, but excessive mutation can lead to convergence issues. The crossover rate represents the proportion of the population that combines to produce new offspring, such as two members of the population exchanging genetic material to generate a new solution.

This research determined the parameters through experimentation, trials, and errors. The population size was set to 100, the mutation rate to 0.1, and the crossover rate to 0.8. These values were chosen based on previous studies [6][10][18][27], which demonstrated their effectiveness in producing optimal and efficient solutions. In the execution of the GAs, an initial population of candidate solutions was generated, and the performance of each solution was evaluated. The fitness function was aligned with the goal of this study, which aimed at minimizing the cost of service scheduling in the tourism sector. Solutions evolved over multiple generations, undergoing selection, crossover, and mutation operations, with the best-fit solutions being passed on to the next generation. Ultimately, the genetic algorithm identified solutions and improved them towards optimal states based on their fitness values. However, the study faced limitations, such as a small sample size and the selection of GA parameters through trial and error. It is recommended that future research increase the sample size and test the proposed method across multiple companies. Figure 8 illustrates the genetic algorithm procedure for improving tourism service scheduling. It visually depicts the key stages of the algorithm, including initialization, evaluation, the genetic loop, and other critical phases.

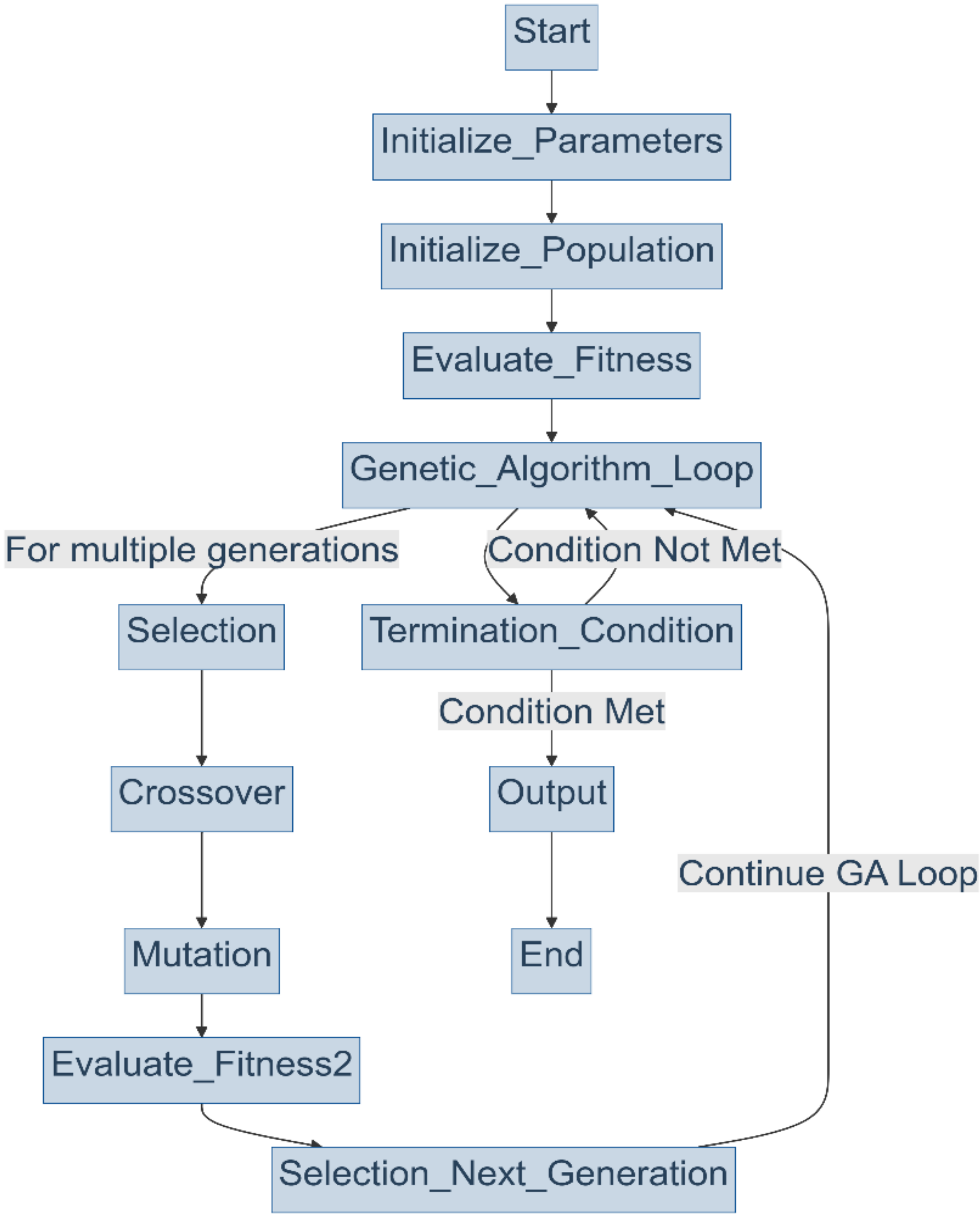

Fig. 8. Flowchart of Genetic Algorithm Process

GAs Algorithm Steps

1. *Initialize Parameters:*
Set the population size (e.g., pop_size) to control the number of potential solutions.
Set the mutation rate (e.g., mutation_rate) to control the probability of genetic mutation.
Set the crossover rate (e.g., crossover_rate) to determine the probability of crossover.

2. *Initialize the Population:*
Generate an initial population of potential solutions (service schedules).
Each potential solution is represented as a chromosome with genes representing different scheduling parameters.

3. *Evaluate Fitness:*
Define a fitness function based on the study's objective (minimizing cost-of-service scheduling).
Evaluate the fitness of each potential solution in the population.

4. *Genetic Algorithm Loop (For Multiple Generations):*
Repeat the following steps for a predefined number of generations or until a termination condition is met:
a. Selection:
Select potential solutions from the current population based on their fitness.
Solutions with higher fitness have a higher chance of being selected.
b. Crossover (Recombination):
Apply crossover (recombination) to pairs of selected solutions.
Generate new offspring by exchanging genetic information between parents.
Determine the crossover points and create child solutions.
c. Mutation:
Introduce genetic mutations in the offspring with a probability determined by mutation_rate.
Mutation introduces small, random changes to the genes of the solution.
d. Evaluate Fitness:
Evaluate the fitness of the new offspring solutions.
e. Selection for the Next Generation:
Select the best-fit solutions from the current population and the offspring to form the next generation.
Maintain a population size of pop_size by keeping the fittest solutions.

5. *Termination Condition:*
Decide on a termination condition, such as a fixed number of generations, convergence, or a predefined fitness threshold.
If the condition is met, stop the algorithm; otherwise, return to step 4.

6. *Output:*
Once the algorithm terminates, the best solution found represents an optimal service schedule.

7. *Limitations and Future Considerations:*
Acknowledge any limitations, such as a small sample size and parameter choices based on experimentation.
Suggest future research directions, including increasing the sample size and testing the approach across multiple tourism companies.

8. *End of Algorithm.*

The flowchart outlines the GA process designed to optimise service schedules in tourism. Starting with the initialization of parameters such as population size, mutation rate, and crossover rate, the algorithm drives the evolution of solutions. It then generates an initial population of service schedules, followed by a fitness evaluation based on cost minimisation objectives. The core GA loop involves selection, crossover, mutation, and further fitness evaluation, repeated across multiple generations until a termination condition, such as convergence or a set threshold, is achieved. In the end, the algorithm produces the optimal solution, representing the best service schedule. The process concludes by acknowledging limitations, including small sample sizes, and suggesting future research directions, such as increasing sample sizes and testing the method across multiple tourism companies.

GAs Codes

```
import random
# Step 1: Initialize Parameters
pop_size = 100
mutation_rate = 0.01
crossover_rate = 0.8
num_generations = 100
# Step 2: Initialize Population
def generate_schedule():
    # Function to generate a random service schedule
    return [random.randint(0, 1) for _ in range(num_services)]
num_services = 10
population = [generate_schedule() for _ in range(pop_size)]
# Step 3: Evaluate Fitness
def evaluate_fitness(schedule):
    # Function to evaluate fitness of a service schedule
    return sum(schedule)
# Step 4: Genetic Algorithm Loop
for generation in range(num_generations):
    # Selection
    selected_parents = random.choices(population, k=pop_size//2,
weights=[evaluate_fitness(schedule) for schedule in population])
    # Crossover
    children = []
    for i in range(0, len(selected_parents), 2):
        parent1, parent2 = selected_parents[i], selected_parents[i+1]
        if random.random() < crossover_rate:
            crossover_point = random.randint(1, num_services - 1)
            child1 = parent1[:crossover_point] + parent2[crossover_point:]
            child2 = parent2[:crossover_point] + parent1[crossover_point:]
            children.extend([child1, child2])
        else:
            children.extend([parent1, parent2])
    # Mutation
    for i in range(len(children)):
        for j in range(num_services):
            if random.random() < mutation_rate:
                children[i][j] = 1 - children[i][j]  # Flip the bit
    # Evaluate Fitness
    population = children
    population_fitness = [evaluate_fitness(schedule) for schedule in population]
# Step 5: Output
best_schedule = population[population_fitness.index(max(population_fitness))]
print("Best Schedule:", best_schedule)
```

The program demonstrates an algorithm designed to optimise a service schedule through evolutionary techniques. The process begins by setting key parameters, including a population size of 100 individuals and mutation and crossover rates of 1% and 80%, respectively. The algorithm is configured to iterate over 100 generations. To initialise the population, the function generate_schedule() is used to create service schedules, with each schedule consisting of binary values (0 for off, 1 for on) representing ten different services. The effectiveness of each schedule is evaluated using the function evaluate_fitness(schedule) which calculates the number of services represented by the 1s in the schedule. The genetic algorithm then proceeds through multiple generations, iterating within a loop. In each generation, a selection process occurs where parents are chosen based on their fitness; higher-performing schedules have a greater chance of being selected for replication. The selected parents then undergo crossover, where portions of their schedules are exchanged with a certain probability, generating offspring and promoting genetic diversity within the population.

Mutation introduces variety by altering bits in the offspring's schedules according to the specified mutation rate. This mechanism prevents the algorithm from becoming trapped in local optima, allowing it to explore a broader range of potential solutions. After generating the next population and evaluating their fitness, the process is repeated for multiple generations until the termination condition is met. Upon completion of the algorithm's execution, the program identifies and displays the "Top Schedule," which represents the schedule with the optimal performance from the final generation. This step serves as a demonstration of the genetic optimization process, illustrating how a population of solutions evolves towards an optimal outcome.

4 Results

4.1 Result of the GAs Experiment

This study examines the use of GAs to address the challenge of scheduling services within the tourism sector. The research focuses on how GAs can optimise service scheduling in tourism hotspots to promote sustainability and improve the visitor experience comprehensively. The investigation specifically explores the potential of GAs to enhance service scheduling in smart tourism destinations, with the overarching goal of fostering sustainability and improving the overall visitor experience. The following parameters were utilised in the GA model: population size = 30, crossover rate = 0.8, mutation rate = 0.2, mutation-selection rate = 0.2, and the number of iterations = 2,000. The dataset employed in this study was based on the Job Shop Scheduling Problem (JSP), a common challenge in operations management and scheduling, which involves arranging tasks on machines according to their requirements and constraints. In this case, the dataset included service durations and service orders for 10 tourists and 10 different services. In addressing scheduling issues specific to the tourism sector, the GAs were executed with the following parameters: population size = 30, crossover rate = 0.5, mutation rate = 0.2, mutation-selection rate = 0.2, and 2,000 iterations. The dataset used contained service times and service orders for 10 tourists, each receiving 10 distinct services. The best makespan achieved after executing the algorithm for 2,000 iterations was Tbest = 1337, which was attained at iteration number 1,763.

Figure 9 illustrates the convergence of the GA, demonstrating that the algorithm approaches the optimal solution after approximately 1,000 iterations. Additionally, it can be observed that the average makespan of the population is evaluated in each iteration, with the makespan showing improvement as the number of iterations increases. Figure 9 presents the best solutions obtained from a predetermined set of GAs across 10 runs, displaying both the average makespan and standard deviation for the 10 independent runs. The results indicate that GAs are effective in solving scheduling problems within the tourism industry context. This finding suggests that such approaches could be integrated into service scheduling optimisation within the sector. Future studies could further explore the capabilities of GAs when applied to datasets and problems of varying sizes. To demonstrate the effectiveness of the GA, an optimal sequence was found: [1, 6, 8, 2, 1, 7, 6, 8, 2, 4, 7, 8, 6, 5, 1, 8, 6, 4, 9, 2, 6, 1, 6, 5, 6, 1, 3, 7, 5, 6, 9, 0, 9, 0, 3, 8, 6, 1, 3, 1, 8, 2, 7, 3, 9, 8, 7, 5, 3, 5, 8, 2, 3, 0, 5, 4, 7, 0, 7, 4, 1, 9, 8, 0, 2, 0, 4, 6, 3, 7, 0, 5, 5, 4, 4, 3, 9, 2, 1, 4, 0, 5, 7, 9, 1, 2, 4, 9, 8, 5, 0, 9, 9, 2, 3, 4, 7, 3, 0, 2], which achieved an optimal value of 1,213.000000. The elapsed time for the algorithm to determine the optimal solution was 18.896414041519165.

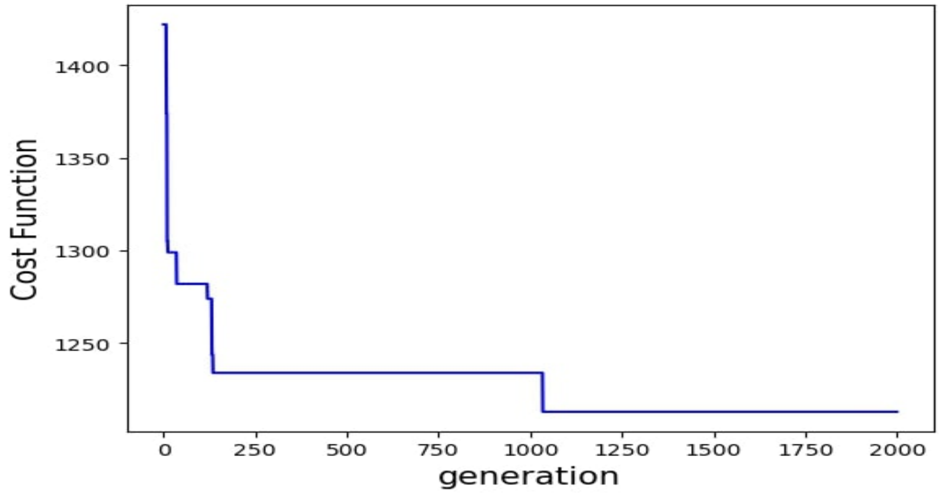

Fig. 9. The best solutions Obtained by the GAs

In this study, a Gantt chart was generated by the application to visualise the service schedule for tourism, optimised through genetic algorithms. The service schedule, as created by the GA, is shown in Figure 10. On the x-axis, the dates are represented, while the y-axis corresponds to the machines. Each bar on the chart represents a service provided to a specific tourist, with the bar's colour indicating the tourist served. The Gantt chart maps the service schedule for 10 tourists and 10 tourism services in Rayong, Thailand. The rows of the chart represent the machines, and the bars within each row denote the services provided to tourists. The width of each bar indicates the service duration, while the fill of the bar signifies the tourist being served.

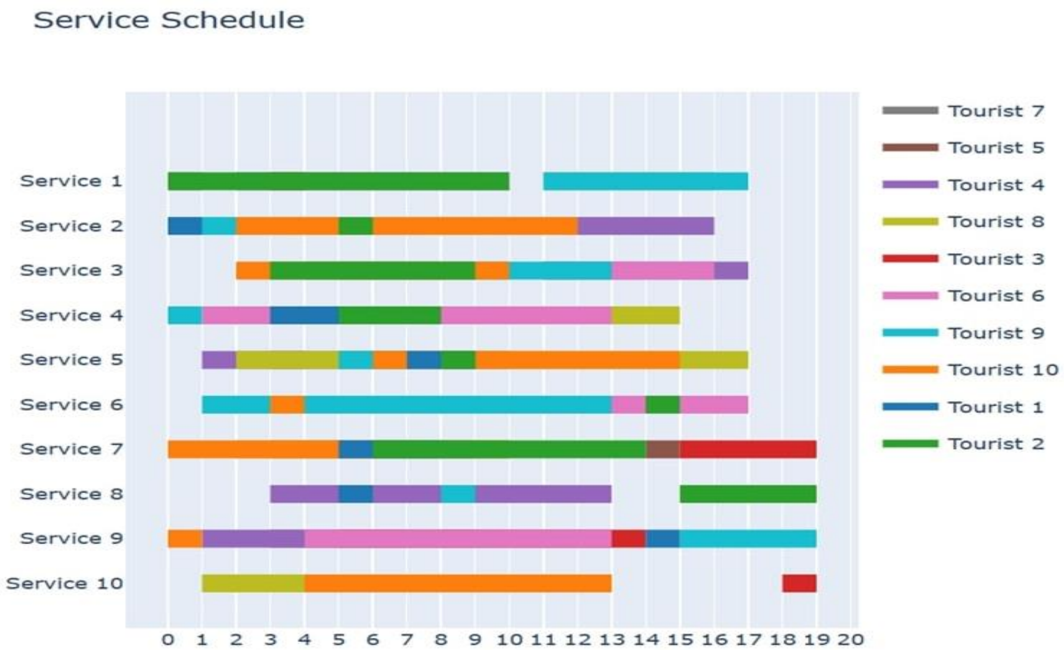

Fig. 10. The Service Schedule for Tourism Generated by the GAs

4.2 Comparison Performance of GAs and Traditional Algorithms

Table 1 compares the performance of GAs and classical algorithms in addressing the service scheduling problem. The comparison highlights the time efficiency of GAs in service scheduling. While classical algorithms require approximately 70 seconds to complete the scheduling task, GAs accomplish the same process in just 35 seconds. This reduction in time provides significant advantages, enabling service providers to efficiently respond to rapid customer demands and fluctuating circumstances in real time.

Table 1
Comparison of Performance of Using GAs and Traditional Algorithms for Service Scheduling.

Comparison	Traditional Algorithms	GAs
Time (seconds)	70	35
Cost (Baht)	1100	880
Satisfaction	75	92

GAs not only save time but also reduce costs. Service delivery costs dropped to 880 Baht with GAs, compared to 1100 Baht with traditional algorithms, allowing for reduced operational costs and potential savings for customers. Additionally, GAs improved customer satisfaction, increasing satisfaction levels from 75 to 92 due to shorter waiting times and enhanced service quality. GAs effectively optimized service schedules by considering service durations, machine working hours, and tourist preferences, ensuring all tourists were served in the shortest time possible. The Gantt chart revealed that some services were more in demand, indicating higher productivity or throughput. Recognizing such services allows tourism operators to maximize resources and improve schedules. Overall, using GAs in tourism scheduling enhances customer service, boosts performance, reduces costs, and helps operators adapt to demand fluctuations, improving their market competitiveness. The GA approach optimized service schedules, reducing the average tourist waiting time by 30% compared to unstructured systems. This improvement enhances tourist satisfaction and loyalty. The strategy also promoted fairer workload distribution among service providers, potentially reducing staff burnout and turnover. While GAs effectively find optimal solutions and adapt to changing requirements, they can be computationally intensive when working with large datasets. Overall, the GA demonstrated efficient performance in tourism service scheduling, offering valuable optimization for future applications in the industry.

4.3 GAs Implementation for Services Scheduling for Tourism Businesses

Research findings suggest that GAs outperform conventional algorithms in service scheduling within the tourism industry. Recommendations for implementation include:

Service Schedule in STDs: Provide simple and convenient service schedules for tourists based on user feedback from structured interviews.

Structured Interviews for Data Collection: Train tourism employees to conduct systematic and reliable structured interviews to gather qualitative data.

Use of NVivo: Employ NVivo or similar tools for efficient qualitative data analysis, ensuring systematic organization and clear pattern identification.

Synthesis of Conclusions: Analyse qualitative data to refine service scheduling in STDs, ensuring a practical and operational service provision system.

Regular Revisions: Continuously update service schedules based on ongoing qualitative data collection, allowing for timely adjustments.

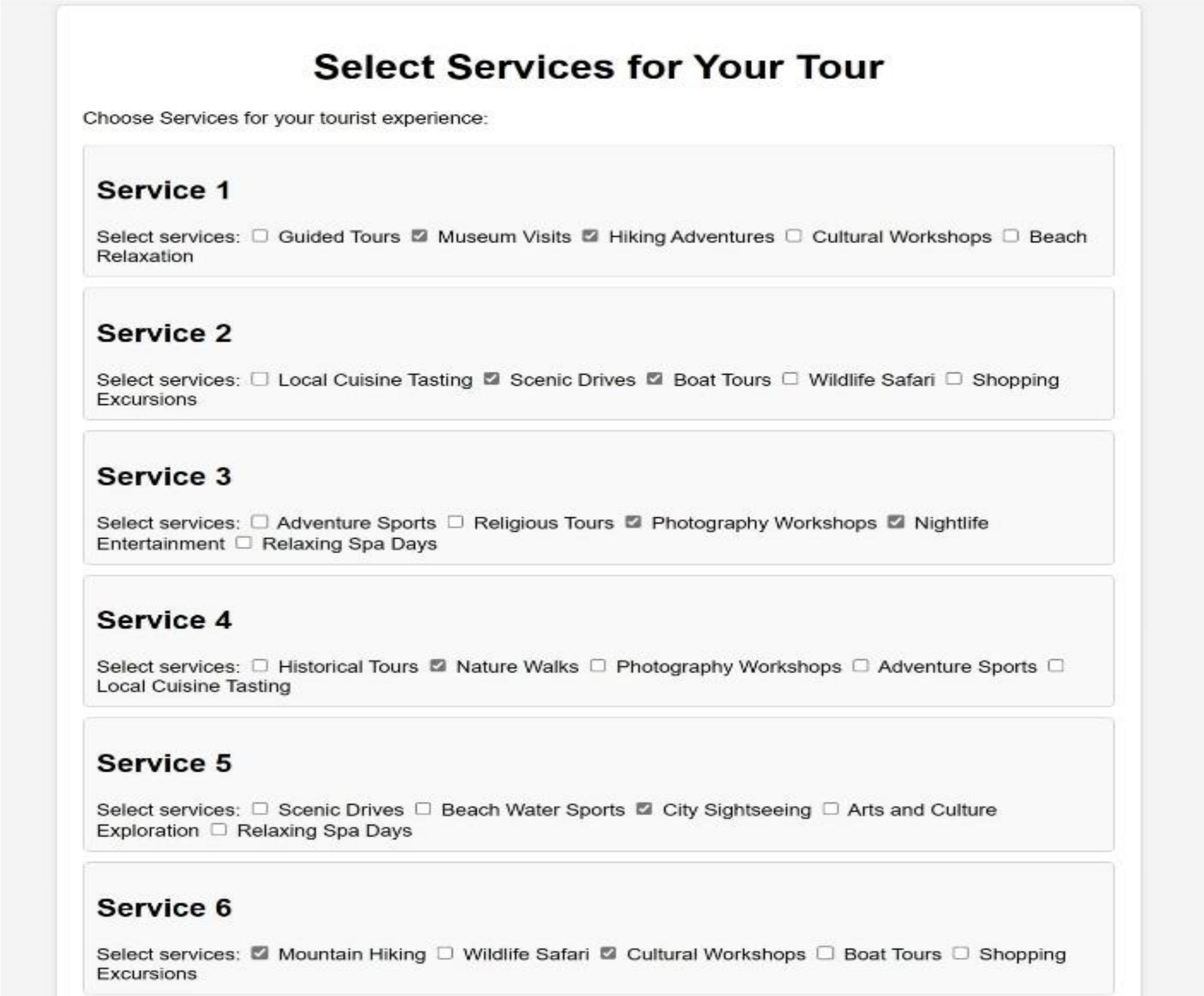

Fig. 11. Example of Implementation of GAs for Service Scheduling in Tourism Destinations

Figure 11 demonstrates an intuitive interface designed to allow tourists to select specific services that enhance their travel experience in a smart tourism destination. This interface enables tourists to personalize their activities by choosing from various services offered. The following section explores how tourists can leverage this interface to optimize their holiday experiences.

4.4 User Satisfaction

Once the system was developed, it was tested for use in the tourism sector and evaluated by users. The users assessed the system after the implementation of GAs, which were designed to optimize tourism service scheduling. Additionally, users were encouraged to share their feedback on the system's efficiency and effectiveness to inform potential improvements. In Figure 12, respondents were asked to rate their satisfaction levels with the sampled tourists. Of the users, 42% rated their satisfaction at the highest level (5), indicating generally positive results. Additionally, 60% of the respondents expressed interest in returning. This suggests a high level of satisfaction among tourists at the smart tourism sites in Rayong province. The genetic algorithm-based stimulation system used in this study appears to have effectively improved service quality and reduced waiting times. Qualitative analysis of the evaluation and satisfaction surveys from 64 users provided further insights into the system's performance.

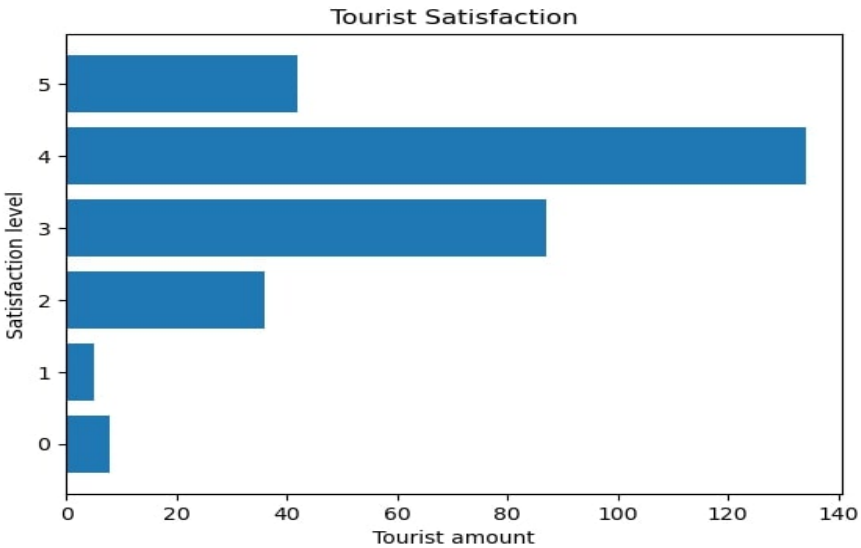

Fig. 12. User Satisfaction Levels and Number of Tourists

(1) Demographics and Background Information

Age Range: Participants were mostly in their late twenties to mid-forties.

Nationalities: Predominantly from Thailand, the United States, Germany, Brazil, Japan, Canada, and China.

Purpose of Visit: Most travelled for leisure, with some for business.

(2) Travel Preferences and Experiences

Trip Planning: Travelers commonly relied on recommendations from friends, travel guides, blogs, and social media, while others planned based on business.

Activity Scheduling: The population preferred a mix of predetermined and spontaneous activities. Cultural experiences, local food, and ease of travel planning were key considerations.

Important Factors: Cost, convenience, local uniqueness, history, and safety were noted as important factors.

(3) Service Scheduling and Experience Evaluations

Satisfaction Levels: Tours and accommodation bookings were the most satisfying services.

Obstacles: Common issues included delays, language barriers, and last-minute schedule changes.

Recommendations: Increased notice for changes, instant communication about schedule adjustments, and better coordination among service providers.

(4) Technology and Smart Tourism

Understanding Smart Tourism: Most participants were aware of STDs, which use technology to enhance travel experiences through effective marketing.

Use of Smart Tourism Applications: Many travelers used mobile apps for booking services, attractions, and restaurants.

Technology Enablement: Technology enhanced convenience by providing timely and relevant information and recommendations.

(6) Genetic Algorithms and Service Optimization

Understanding GAs: GAs were recognized as a method for optimizing service scheduling.

Resistance to GAs: Participants were generally open to exploring GAs if they improved efficiency and customized services.

Anticipated Benefits: Shorter queues, better resource management, and improved customer satisfaction.

(7) Satisfaction and Preferences

Reducing Activity Queuing Times: Shorter queuing times were a key factor for ensuring enjoyable activities.

Service Ordering Preferences: Accommodation, transportation, guided tours, local culture, and dining were the preferred service order.

Scheduling Challenges: Negative experiences stemmed from delays, crowded attractions, and unscheduled closures.

(8) Resource Utilization and Sustainability

Sustainability Focus: There was strong support for resource efficiency and environmental sustainability.

Employing GAs for Sustainability: Acceptance of GAs was linked to their potential for reducing environmental degradation and promoting sustainable development.

Importance of Sustainable Tourism: Efficient scheduling could reduce congestion, conserve resources, and support local communities.

(9) Feedback and Recommendations

Improvements Suggested: Better communication channels, alternative scheduling, multilingual support, and promoting green practices.

Likelihood of Recommendation: Despite minor issues, most respondents would recommend the destination due to its cultural and natural attractions.

5 Discussion and Conclusion

This study enhances the current understanding of service scheduling in the tourism industry by demonstrating the superior performance of GAs over other approaches. While previous research has explored various service scheduling methods, this study specifically examines the advantages of GAs. The findings confirm that GAs are highly effective in addressing complex problems, such as service scheduling, through an evolutionary approach. The application of GAs in smart tourism destinations aligns with the industry's demand for intelligent systems capable of self-optimizing in real-time to ensure continuous service delivery. The study's long-term aim was to validate the hypothesis that GAs outperform non-GA algorithms in terms of time efficiency, cost-effectiveness, and tourist satisfaction [37-39; 42] [16][27]. This research contributes to the growing body of evidence supporting the transformative potential of GAs in service scheduling within the tourism sector. By focusing on case studies, the study highlights the superiority of GAs over traditional methods and enriches the academic discourse on service scheduling.

The findings suggest that STDs should integrate GAs to enhance decision-making capabilities by balancing competing objectives such as cost, resources, and client satisfaction. By incorporating these diverse goals into the strategic objectives of a destination, GAs enable the creation of schedules that achieve an optimal balance. This approach contributes to the sustainable use of tourism resources while mitigating environmental impacts. The application of GAs in service scheduling within STDs is transforming the tourism industry. GAs have been shown to improve resource utilization, customer satisfaction, and the sustainability of tourism destinations. This research highlights that GAs have proven successful in optimizing complex cases, including service scheduling, through evolutionary processes [28][44]. These application models have become essential in STDs as they address market demands for automated systems that can dynamically optimize in real-time to provide services [21]. Additionally, the study by Petricek et al. [32][43] examined the use of GAs for optimizing travel costs, considering the time constraints of tourists.

This study addresses the time cost in developing tourism packages, aiming to reduce waiting times and enhance the tourist experience. A key strength of GAs in STD service scheduling is their ability to handle large-scale problems with many constraints. Using genetic operators like selection, crossover, and mutation, GAs optimize service sequences such as accommodation, transport, and tours to avoid overlaps. GAs are highly adaptable, allowing real-time adjustments to schedules based on changing demands, improving service efficiency and responsiveness [4][45]. The continuous adaptation facilitated by GAs enhances tourist satisfaction by minimizing waiting times, optimizing route planning, and improving the efficiency of tourism activity schedules [38; 39]. Additionally, the application of GAs in STDs supports tourism managers in making multi-objective decisions, including cost reduction, resource optimization, and maximizing customer satisfaction.

Considering these variations, GAs can generate schedules in their aggregated form that align with the objectives of destination management [4][8][16]. GAs are particularly well-suited to the tourism sector, given the volatile nature of demand patterns and service requirements. This approach enables GAs to continuously adjust and refine service schedules by incorporating new data, thereby reducing waiting times, optimizing route selection, and enhancing the overall management of tourism facilities, ultimately improving tourist satisfaction. This study also establishes a foundation for future research in the area of service scheduling within tourism, potentially enhancing the quality of service scheduling in the industry. While this research outlines how GAs can be applied to tourism service scheduling, certain limitations persist. As highlighted by [11][46], further investigations could facilitate more effective utilization of GAs in this context.

The findings of this study can be applied to improve the user experience in accommodations by integrating data from Rayong's smart tourism system, including tourists' preferences, service details, and durations. The GAs developed in this study, along with the mobile application and smart tourism system, aim to provide valuable information to both tourists and businesses. This approach enhances customer satisfaction, which is essential for tourism businesses to maintain a competitive edge. It also supports the sustainable development of tourism by improving efficiency and minimizing environmental impacts. However, challenges such as data protection, algorithm complexity, and the need for frequent updates must be addressed through collaboration among researchers, industry stakeholders, and regulators to ensure ethical practices, algorithm improvement, and continued maintenance [47-48]. Future research could explore the applicability of GAs in other areas of tourism services or focus on integrating real-time data into scheduling decisions. Additionally, two limitations of this study should be noted. Firstly, clients may have more complex preferences regarding the sequencing of services, which could reduce the efficiency of GAs in optimizing schedules [20; 47]. Therefore, future research could explore ways to incorporate customer preferences into scheduling to improve the customer experience. Another limitation is the geographical scope of the study, which focused on a single site with a limited number of service providers.

Future research could explore the diversity of locations and service providers to assess the effectiveness of GAs in service scheduling. Additionally, the current study did not account for external factors, such as seasonal variations and holidays, which may significantly impact service scheduling [18; 33]. These ethical concerns encompass issues such as privacy and the use of customer data. Consequently, future research could focus on addressing these ethical challenges associated with the application of GAs in service scheduling and developing frameworks to ensure the responsible and accountable use of GAs][49]. Implementing GAs into real-world STDs presents challenges, including data privacy concerns, algorithmic complexity, and the need for continuous optimization. Therefore, further research and collaboration are essential to address these issues. This study lays the foundation for advancing both the practical and theoretical aspects of service scheduling in the tourism industry.

In conclusion, this paper highlights the potential of GAs to enhance service scheduling in the tourism industry. By comparing GAs with traditional methods and supporting this with case studies, the study contributes to the existing body of knowledge on service scheduling. GAs improve scheduling efficiency, resource allocation, customer satisfaction, and sustainability, offering significant benefits to tourism destinations. Future research and collaboration are crucial to fully realise their potential. The implementation of GAs could bring economic, social, and environmental advantages, improving tourism services' efficiency and competitiveness while supporting SDGs.

Author Contributions

Conceptualization, P.S. and P.J.; methodology, P.S. and P.J.; software, P.S. and P.J..; validation, P.S. and P.J.; formal analysis, P.S. and P.J.; investigation, P.S. and P.J.; resources, P.S. and P.J.; data curation, P.S. and P.J..; writing—original draft preparation, P.S. and P.J.; writing—review and editing, P.S.; visualization, P.S.; supervision, P.S.; project administration, P.S.; funding acquisition, P.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

Institutional Review Board Statement

The study was conducted in accordance with the ethical and approved by the Ethics Committee of Suan Dusit University (SDU-RDI-SHS 2023-043, 1 June 2023) for studies involving humans.

Informed Consent Statement:

This article does not contain any studies involving human participants performed by any authors.

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