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Tourist route optimization with a combined A* algorithm and genetic algorithm

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This article contributes to the optimization of routes and circuits, aiming to enhance the overall tourist experience in alignment with smart tourism objectives. Employing advanced techniques and tools like A*, genetic algorithms, and geographic information systems, the study aims to propose highly efficient paths for city exploration and touristic attraction visits. It outlines future projections in optimization tools, attempting to integrate artificial intelligence and machine learning technologies to create customized itineraries based on user preferences. Acknowledging the existing limitations in the field, the article provides a new solution characterized by optimized costs and reduced execution time. With its primary focus on the city of Fez, the article aims to enhance smart tourism applications by offering personalized and enriched experiences.

Keywords: *smart tourism; routing approaches; route optimization; geographic information system (GIS); point of interest (POI); A* algorithm; genetic algorithms.*

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1. Introduction

Tourism is a rapidly rising business with a substantial worldwide economic impact. In 2018, the number of international tourists reached 1.4 billion according to the World Tourism Organization, and this figure is anticipated to increase further in future years [1]. As the tourism sector grows, there is an increasing demand for innovative solutions to improve the travel experience for tourists. Tourism is a fiercely competitive sector, with travel destinations competing for tourists' attention and money. To stay competitive, destinations must constantly innovate and enhance their tourist experience. The optimization of travel routes has attracted increased amounts of attention in recent years because of its purpose of designing effective and personalized routes and circuits that make the best use of available time and resources while providing visitors with a memorable experience. This is crucial in the context of smart tourism, which uses technology to improve the travel experience and provide visitors with individualized recommendations [2]. Route optimization is the process of using data and technology to design tourist travel routes that are effective and entertaining [3]. Destinations and attractions can offer more individualized and gratifying travel experiences to visitors while also making the best use of their time and money by optimizing travel routes. However, with technological innovations, geospatial data availability, and the development of smart city concepts, it is now possible to create intelligent algorithms that can suggest optimal tourist routes, considering various factors such as historical landmarks, cultural sites, popular attractions, walking distances, and local recommendations [4]. In our last contribution to the field of smart tourism application, we made a first attempt to provide an optimized touristic circuit using the heuristics of the genetic algorithm and Bing Maps API applied to the city of Fez, but we encountered some limitations that made the pursuit of some improvement necessary to overcome high-cost and technical problems [5].

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In this article, we will try to provide a new way to build and recommend optimal tourist circuits. We hope that by doing so, we may contribute to efforts to create technological tools that can be used to improve tourist experiences and encourage sustainable tourism practices. Our suggested method has the potential to transform the way destinations organize and promote travel itineraries, hence increasing destinations' competitiveness in the global tourist market. This paper begins by reviewing the relevant literature and existing heuristic tools that can be used in tourist route optimization. We will then present the methodology used for data collection and analysis, including the integration of geospatial data, tourist preferences, and local knowledge. Furthermore, we outline the method and approach used to produce efficient and personalized itineraries for the proposed tourist route optimization for the case study framework of the Old City of Fez. The framework will be evaluated using real data. As previously stated, the fundamental purpose of this research paper is to propose and build a novel tourist route optimization system. We hope to suggest an approach that truly enhances the entire experience of tourists and creates a real smart touristic journey to discover a certain city and its attractions by utilizing computational algorithms, geographical data analysis, and tourist preferences. We predict that the suggested methodology will contribute to sustainable tourist growth, greater visitor satisfaction, and the preservation of a city's cultural heritage by improving the visitor experience through effective path planning.

2. Literature review

The important methods that can be applied to planning and improving tourist routes are summarized and presented in this section. For reference, various techniques are addressed and outlined in this context.

2.1. Evolutionary smart local search

Genetic algorithms traced their origins back to John Holland's groundbreaking work in the 1960s, which laid the foundations for the evolution of solutions through natural selection and genetic operations. Since then, genetic algorithms have evolved and found a variety of applications, including pathfinding, optimization and others [6–8]. Genetic algorithms involve a set of fundamental equations, the cornerstone of which is the fitness function, which quantifies the quality of a solution (x):

$$\text{Fitness}(x) = \text{Evaluation}(x),$$

where $\text{Evaluation}(x)$ represents the efficiency of the solution. In pathfinding applications, genetic algorithms excel at encoding problems as sets of genes and then use genetic operations such as crossover and mutation to iteratively refine these solutions. The success of genetic algorithms depends on the meticulous encoding of genes. In path-finding problems, individual genes can represent the sequence of traversed nodes. Crossover facilitates the exchange of information between parent solutions, generating top-down solutions, while mutation randomly modifies solution genes, introducing potentially beneficial variations. The effectiveness of genetic algorithms depends on the genetic operators chosen (crossover and mutation rates), the design of the fitness function, the size of the population and the number of generations [9]. In particular, genetic algorithms find fertile ground in intelligent tourism applications, where they optimise travel itineraries according to factors such as desired attractions, travel time constraints and user preferences [10]. Genetic algorithms can be adapted to discover optimal routes that will evolve to better solutions/routes over time. Encoding the problem as a set of genes is crucial to the success of genetic algorithms.

The new top solutions substitute for the former bad ones in the succeeding generations.

Initialization. The first generation is performed in a random way, allowing to cover the wide spectrum of all possible solutions [8, 11–13]. Sometimes, solutions can be separated into regions where the best solutions are likely to be achieved. Let's $D = I_1 \times I_2 \ldots \times I_n$ be a domain containing all the feasible solutions of our problem. A numerical technique permitting to generate an uniform initial solutions consists on decomposing I_i using an appropriate step (said h_i). In this case, the feasible nodes $(n_{p_1,\ldots,p_n})$ of the considered discretisation constitute the initial population, where

$$n_{p_1,\dots,p_n} = (p_1h_1, \dots, p_nh_n).$$

In this equation $p_ih_i \in I_i$ and $p_i \in \mathbb{N}$.

Fitness function. To create an appropriate fitness function, it is important to adopt a number of good practices simplicity, reproducibility, and iterative development [14]. The most commonly used formula is given by

$$\text{Fitness} = (\text{weight}) * (\text{Objective\_function}) - \text{Penalty} * (\text{Constraint\_infringed}).$$

Selection. In each following generation, a subset of the surviving population is screened to breed a newer generation [15]. The main screening techniques include roulette wheel selection and rank selection.

Roulette wheel selection: linear ranking is often used. It allows the selection pressure to be set by the parameter s, with values between 1.0 (no selection pressure) and 2.0 (high selection pressure). The probability of rank positions is given by

$$P(R_i) = \frac{1}{N}\left(s - (2s-2)\frac{i-1}{N-1}\right),$$

where $1 \leqslant i \leqslant n$ and $1 \leqslant s \leqslant 2$ and N is the size of the current population.

Rank selection: probability of choosing individual i is equal to $p_i = f_i/(\sum_{j=1}^{N} f_j)$, where f_i is the fitness of i and N is the size of the current population.

Crossover is a genetic process that aims to merge the DNA data of two individuals in order to breed a new child [15]. In our case, we use multiple crossover, applied to 80% of the population with a given ratio (R). Given two parents $parent_1$ and $parent_2$, a child $child$ is obtained by

$$child = parent_1 + rand * R * (parent_2 - parent_1),$$

where $rand$ is a random real number from [0 1].

Mutation. This operator creates a kind of diversity in the population that helps to avoid bad local minima. There are several types of mutation (for example, uniform mutation, Gaussian mutation and heuristic mutation). We examine the use of the evolutionary algorithm to optimize tourist routes in this research, outlining the advantages and limitations [16]. We further discuss the efficiency of this approach in terms of route optimization [17].

2.2. A* algorithm

The A* algorithm was initially proposed by Hart, Nilsson, and Raphael in 1968. Since then, it has been applied in a wide range of fields, including the planning of touristic routes [18]. A* is a Dijkstra's algorithm extension that combines components of the best-first and breadth-first search methods, enables particularly adept at finding optimal paths while taking heuristic information into account. By using a heuristic-driven approach, the algorithm is able to efficiently explore the search space and find the best solution in a significantly shorter computation time. In its basic form, the A* algorithm depends on two elements: the cost function and the heuristic function. The cost function $f(n)$ estimates the total cost of the optimal path from the starting node to a given node n by combining the actual cost from the starting node to n $g(n)$ and the estimated cost from n to the goal node $h(n)$:

$$f(n) = g(n) + h(n).$$

These functions are used by A* to intelligently explore the search space, giving lower f(n) nodes priority and effectively guiding the search toward the optimal solution. The commonly employed heuristic options often involve using the Manhattan distance, which calculates the total of absolute coordinate variations and is typically suitable for grid-like structures. Alternatively, the Euclidean distance, which measures the straight-line distance, is frequently used for continuous environments [19].

The A* algorithm shows its utility in its application to tourist itinerary optimization by identifying the best route while considering various factors, such as attraction appeal, time, and distance. Researchers have customized the A* algorithm by including heuristics related to tourism, such as user preferences, popularity of attractions, and geographical constraints [20]. For instance, when attempting to suggest an optimal route that balances travel distance and tourism value, a heuristic function might take into account both the distance between touristic sites and their attractiveness ratings. The details of the A* algorithm are provided in Algorithm 1.

Algorithm 1 A* algorithm used in this work.

// Initialisation step
OpenList: $O \leftarrow \{s\}$
ClosedList: $C \leftarrow \{\}$
// Cost function initialisation
$g(s) = 0$ // since the cost from the start to itself is 0
$h(s)$
while $O \neq \varnothing$
    // the Main Loop of A*
    Select the node $n \in O$ with the lowest $f(n) = g(n) + h(n)$ value
    if n is the goal **then**
        Reconstruct the path
        return (path)
    else
        for each successor m of n
            Compute $g(m) = g(n) + \text{cost}(n, m)$
            Compute $h(m)$ // heuristic estimate from m to goal
            Compute $f(m) = g(m) + h(m)$
        for each successor m
            if $m \in C$ and $g(m) \geqslant g(e)$ **then**
                // e is the existing successor
                Skip m
            if $m \notin O$ **then**
                $O \leftarrow O \cup \{m\}$ // add m to O
            else if $m \in O$ and $g(m) < g(e)$ **then**
                Update $g(m)$
                Recalculate $f(m)$
        $C \leftarrow C \cup \{n\}$ // add n to C // Node Closure step
        if goal is not reached and $O = \varnothing$ **then**
            return (no path)

2.3. Geographic information systems

Finally, in this field, geographic information systems are used to optimize tourist routes, and GIS allows for the effective administration, analysis, and display of geographical data pertaining to points of interest, transit networks, and other important elements. By using GIS tools and techniques, researchers and practitioners may construct sophisticated algorithms and models that consider many variables, such as distances, trip durations, traffic conditions, and visitor preferences [21]. GIS has various advantages for planning tourism routes or circuits; it enables the integration of many data sources, such as geolocation data, tourist behaviour data, and real-time information, allowing for thorough and dynamic analysis. Second, GIS make it easier to identify the best routes by considering not only distances but also characteristics such as attraction popularity, accessibility, and temporal connections. Furthermore, a GIS allows for the display of outcomes by offering interactive maps and visual representations that improve decision-making and communication with stakeholders [22].

This paper proposes a full approach to optimizing tourist routes and circuits that combines GIS, the genetic algorithm and the A* algorithm. We hope to create a solid and efficient framework for generating and improving tourist itineraries by combining these various methodologies. This study seeks to provide a complete and extensible strategy for optimizing tourist routes and circuits by integrating GIS, the evolutionary algorithm and the A* algorithm. We hope to demonstrate the usefulness and application of this integrated technique for improving tourist experiences, supporting sustainable tourism practices, and encouraging efficient resource allocation through empirical research and assessment.

3. Proposed approach

Fez was chosen as our smart tourism contribution hub and as the focus point for data collection due to its prominence as one of Morocco's most famous touristic cities, notably its historical medina, which is recognized as the world's largest car-free urban area. To provide a thorough and representative dataset, 74 points of interest (POIs) were chosen for data collection. The dataset used in the following applications and tests comprises 2707 nodes from Fez's Old Medina, confirming the relevance and correctness of the results. The data were collected during the period from March to May, which is a period of considerable fluctuation and the peak tourist season in Fez. It is worth mentioning that the data collection took place during the revival of the city's tourism sector, following a two-year period of severe limitations due to the COVID-19 pandemic. This window of opportunity allowed for the assessment of new dynamics and trends in the city's tourist sector.

We performed a set of experiments on the dataset using various tool combinations to assess the effectiveness of each recommendation in optimizing the circuit primarily in terms of distance while ensuring that the results were delivered within a reasonable execution time frame. In our previous paper, we introduced the use of the genetic algorithm in conjunction with the Bing Maps API. Building upon that, this paper expands on optimization techniques by employing both the genetic algorithm and the A* algorithm.

The mentioned tests will be carried out on a collection of 15 points of interest (POIs), as shown in Table 1, each with its own ID. These 15 POIs were chosen after consulting with local guides and considering the highest possible count of POIs that a tourist could visit in a single day. Furthermore, the POI list was thoughtfully selected to cover some of the most engaged sites within Fez's historical Medina. These choices were determined using suggestions from trustworthy sources such as TripAdvisor, as well as other apps and surveys. Another essential consideration in the selection process was the enduring impression produced by each POI. These specific POIs are the ones most warmly recalled by tourists following their visit to Fez, according to inputs and feedback from local guides and data surveys.

Table 1. Test POIs.

POI	ID	Latitude	Longitude
Jenan Sbil	JS	34.0600149	−4.9875509
Bab Boujloud	BB	34.0616817	−4.9840568
Batha Museum	MBA	34.0602058	−4.9827331
Belghazi Museum	MBE	34.0638983	−4.9763294
Alqaraouine Library	BA	34.0642525	−4.9728404
Bab Elguissa	BE	34.0691503	−4.9758189
Moulay Idriss	MI	34.064718	−4.974954
Bab Ftouh	BF	34.0600152	−4.96492
Sidi Ahmed Tijani	SAT	34.0663754	−4.9735924
Ennejarin Museum	ME	34.0647942	−4.9758579
Rssif Mosque	MR	34.0626764	−4.973418
Bab Sidi Boujida	BSB	34.0668303	−4.9661479
Palais El Glaoui	PEG	34.0588653	−4.9771708
Mederssa Cherratine	MC	34.0641862	−4.9737061
Mederssa Seffarine	MS	34.0638068	−4.9727539

In this proposed approach, we use the genetic algorithm to generate the range of the population of possible solutions (mutations, crossing, etc.); then, we proceed to the test of fitness according to the A* algorithm. Thus, to obtain the fitness function through A*, we need a certain kind of data input, which includes the different touristic locations (points of interest; POIs) as well as the pathways between these locations.

The genetic algorithm's configuration details are provided in Table 2 below, highlighting key parameters such as the crossover rate (the likelihood of chromosome swapping, representing circuits), the mutation rate (indicating the probability of circuit alteration), the maximum number of generations and the minimum fitness threshold for a circuit. The chosen parameters for the genetic algorithm were adjusted to balance exploration and exploitation in determining the order of visiting tourist POIs.

Table 2. Parameters of the Genetic Algorithm.

Parameter	Value	Description
Crossover rate	0.6	The probability of two chromosomes exchanging genetic information. Crossover involves the selection of random genes from the chromosomes and subsequently swapping all genes beyond that point
Mutations rate	0.1	The probability that a single bit within a chromosome undergoes a flip or change
Min fitness	0	The adaptation value needed to attain an optimal level of fitness
Generations	200/500	Number of generations

With a crossover rate of 0.6, the algorithm prioritizes diverse combinations of visit sequences, fostering exploration to discover various tour routes. Similarly, a mutation rate of 0.1 allows controlled alterations, slightly adjusting the visit order without deviating significantly from potentially efficient sequences. By setting the minimum fitness condition to the best visit order, the algorithm aims to identify the most advantageous itineraries. We experimented with two numbers of iterations, 200 and 500, to assess the significant impact of the number of iterations on the results obtained, aiming to better understand its influence on the quality of the generated tour routes.

To be able to source the data input for the A* algorithm, we used a collaborative GIS named OpenStreetMap, from which we first extracted pathways (in shape format) in the test zone of the Old Medina of Fez; then, we imported the data into the spatial databases (PostGis extension to be able to read geospatial data; PostgreSQL to manage the database as a whole).

Once the importation was complete, a problem was noticed regarding the intersections, a problem that could have distorted the results and misrepresented reality, e.g., we have a pathway going under a bridge. On the map, an intersection point that is not a real intersection can be observed; thus, we cannot suggest that the user on the bridge go left or right on the road because it does not correspond to any real route. Thus, for similar cases where there are bridges or underground pathways, we proceeded to data management by breaking down and slicing the itinerary into two or more pathways and hence creating identified nodes (vertices) in the extremity of each pathway that identifies each route between a given starting and arrival point.

The next step was geocoding the collected field data (Fez Old Medina). The data were regrouped in Excel sheet format according to name, address, and attribute range (X, Y (latitude and longitude)); geocoding consists of converting these attributes into geospatial data, which constitute the input for the algorithm (pathways and POIs). Once the A* algorithm is provided with the input, we can proceed with the process and iterations to define the critical route/path.

To be more specific with an illustration from our context, we have obtained the starting/departure points with a number N of POIs that we are going to visit combined with the pathways and vertices (nodes) data from the databases; the first thing that will be executed is to locate and link the POIs (that are not on the pathways) to the actual pathways on the map. This task was performed by locating the nearest node (vertex) to the POI, creating a direct link and adding it to the map so that the whole graph would always be closed. Once the graph (circuit) is closed, we inject the data into the A* algorithm. A spatial intersection between point A and point B was performed to define potential pathways between two points, after which the critical pathway was ultimately selected.

The chosen heuristic function for our experimental test in the A* algorithm was the Manhattan distance, often referred to as $h(n)$. The Manhattan distance between two points is given by

$$h(n) = |xgoal - xn| + |ygoal - yn|,$$

where $(xgoal, ygoal)$ represents the coordinates of the goal node, and (xn, yn) represents the coordinates of the current node. The workflow of the proposed smart algorithm is illustrated in Figure 1.

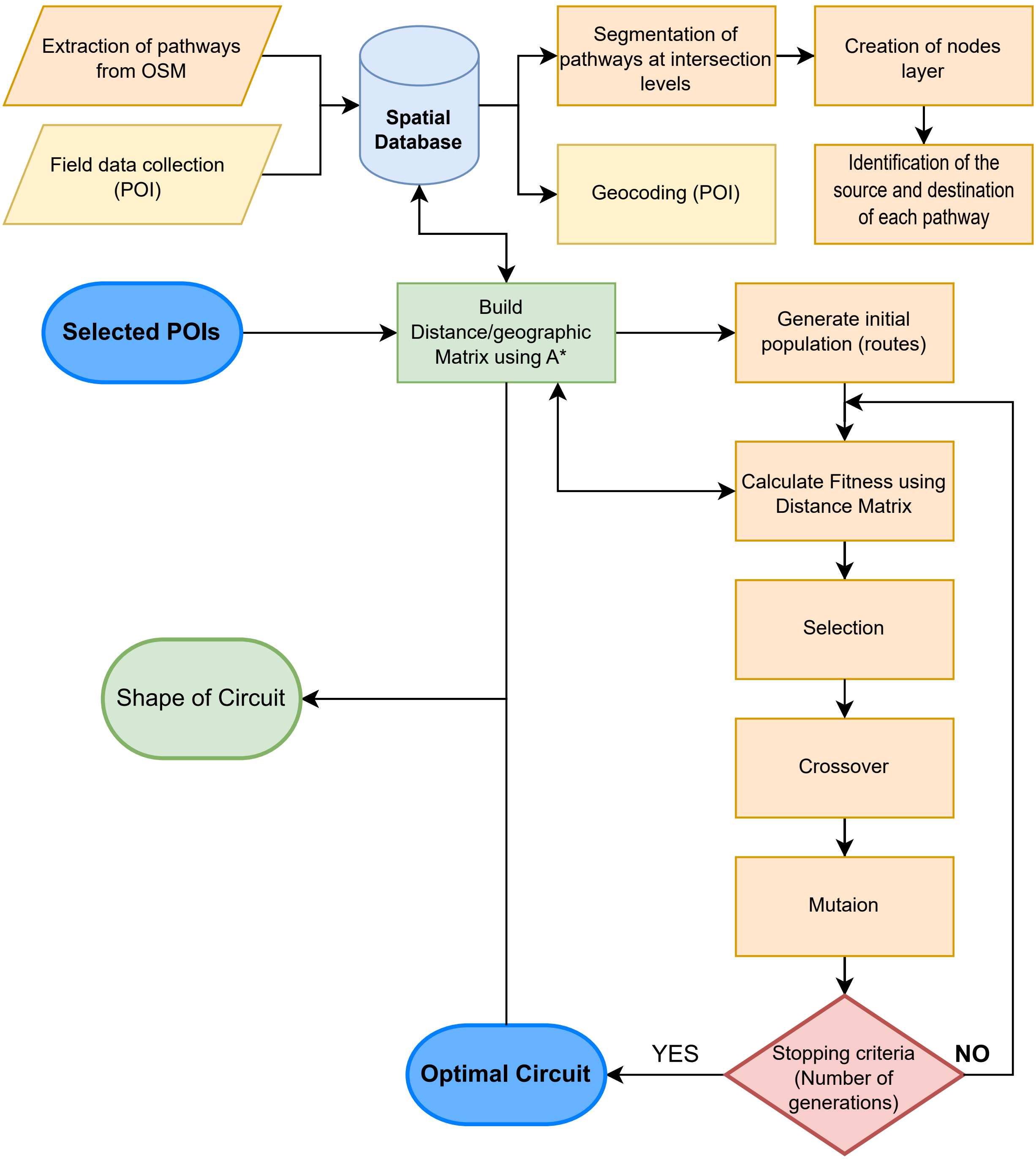

Fig. 1. Workflow of the proposed approach.

4. Experimental test and results

The experimental tests were conducted using a Core i7 laptop equipped with 8 cores, 8 GB of RAM, and an HDD hard drive. The laptop was connected to a network with a download speed of 2 Gb/s and an upload speed of 1 Gb/s, utilizing an optical fiber connection.

Please consult Table 1 for details of the test series conducted on a selection of 15 points of interest (POIs). It is important to note that this number was determined based on suggestions from local guides regarding the maximum number of points of interest (POIs) a tourist can explore in one day. The results of our proposed method are presented below.

Table 3. Results of Genetic algorithms and A*.

NP	ET	Dist	Route	Iters
15	4.80	9.34	BB-BE-BSB-BF-BA-MR-MS-MC-SAT-MBE-ME-MI-PEG-MBA-JS-BB	200
15	4.80	9.24	BB-JS-MBA-MR-MS-BA-MC-SAT-MI-MBE-ME-BE-BSB-BF-PEG-BB	200
15	4.81	8.81	BB-JS-BE-SAT-MI-ME-MBE-MS-MC-BA-BSB-BF-MR-PEG-MBA-BB	200
15	5.03	8.48	BB-JS-MBA-PEG-MR-MS-MC-BA-BF-BSB-BE-SAT-MI-ME-MBE-BB	500
15	5.06	8.98	BB-MBA-PEG-MBE-ME-BE-SAT-BA-MC-MS-BSB-BF-MR-MI-JS-BB	500
15	5.06	9.13	BB-JS-MBA-PEG-MR-MS-SAT-BE-ME-MI-MC-BA-BSB-BF-MBE-BB	500
12	3.36	8.05	BB-JS-MBA-MBE-ME-BE-SAT-MI-BA-BSB-BF-MR-BB	200
12	3.52	8.05	BB-JS-MBA-MBE-ME-BE-SAT-MI-BA-BSB-BF-MR-BB	200
12	3.27	8.01	BB-JS-MBA-MBE-MR-BF-BSB-BA-SAT-BE-MI-ME-BB	200
12	3.43	7.77	BB-JS-BE-SAT-BSB-BF-MR-BA-MI-ME-MBE-MBA-BB	500
12	3.42	7.75	BB-JS-MBA-MBE-ME-MI-BA-MR-BF-BSB-SAT-BE-BB	500
12	3.56	7.86	BB-JS-MBA-MBE-MI-BA-MR-BF-BSB-SAT-BE-ME-BB	500
10	2.29	7.20	BB-JS-MBA-ME-BE-SAT-BA-BF-MI-MBE-BB	200
10	2.40	7.07	BB-JS-MBA-MBE-ME-MI-BF-BA-SAT-BE-BB	200
10	2.38	7.07	BB-JS-MBA-MBE-ME-MI-BF-BA-SAT-BE -BB	200
10	2.75	7.18	BB-ME-BE-SAT-BA-BF-MI-MBE-MBA-JS-BB	500
10	2.45	7.20	BB-JS-MBA-ME-BE-SAT-BA-BF-MI-MBE-BB	500
10	2.46	7.09	BB-JS-BE-SAT-BA-BF-MI-ME-MBE-MBA-BB	500
8	1.55	6.88	BB-BE-SAT-BA-BF-MBE-MBA-JS-BB	200
8	1.71	6.88	BB-JS-MBA-MBE-BF-BA-SAT-BE-BB	200
8	1.61	7.05	BB-JS-MBA-BE-SAT-BA-BF-MBE-BB	200
8	1.74	6.90	BB-JS-BE-SAT-BA-BF-MBE-MBA-BB	500
8	1.68	6.90	BB-JS-BE-SAT-BA-BF-MBE-MBA-BB	500
8	1.67	7.05	BB-JS-MBA-BE-SAT-BA-BF-MBE-BB	500
5	0.63	4.12	BB-BA-MBE-MBA-JS-BB	200
5	0.62	4.12	BB-BA-MBE-MBA-JS-BB	200
5	0.62	4.12	BB-JS-MBA-MBE-BA-BB	200
5	0.71	4.12	BB-JS-MBA-MBE-BA-BB	500
5	0.71	4.12	BB-JS-MBA-MBE-BA-BB	500
5	0.73	4.12	BB-BA-MBE-MBA-JS-BB	500

Legend of Table 3:

— **NP** is the number of selected POIs,
— **ET** is the execution time in seconds,
— **Dist** is the distance in KM,
— **Iters** is the number of iterations.

As the APIs were not needed to extract the distances between POIs, the execution time was considerably shorter, the circuits contained an average of 10 POIs to visit, and the execution time ranged between 2 and 3 seconds on average.

The chart below depicts a noticeable correlation between the number of POIs and execution time, as expected: the greater the number of points of interest (POIs) is, the greater the execution time.

Snapshots of different suggested circuits are mapped below.

The suggested critical circuit for 15 POIs was proposed within 5 second timeframe and had an approximate length of 9 km.

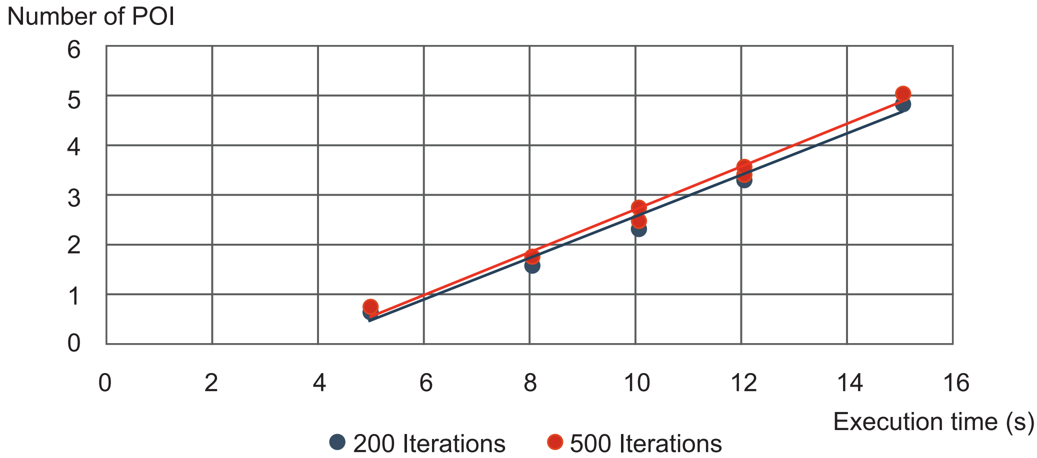

Fig. 2. Correlation between the number of POIs and execution time.

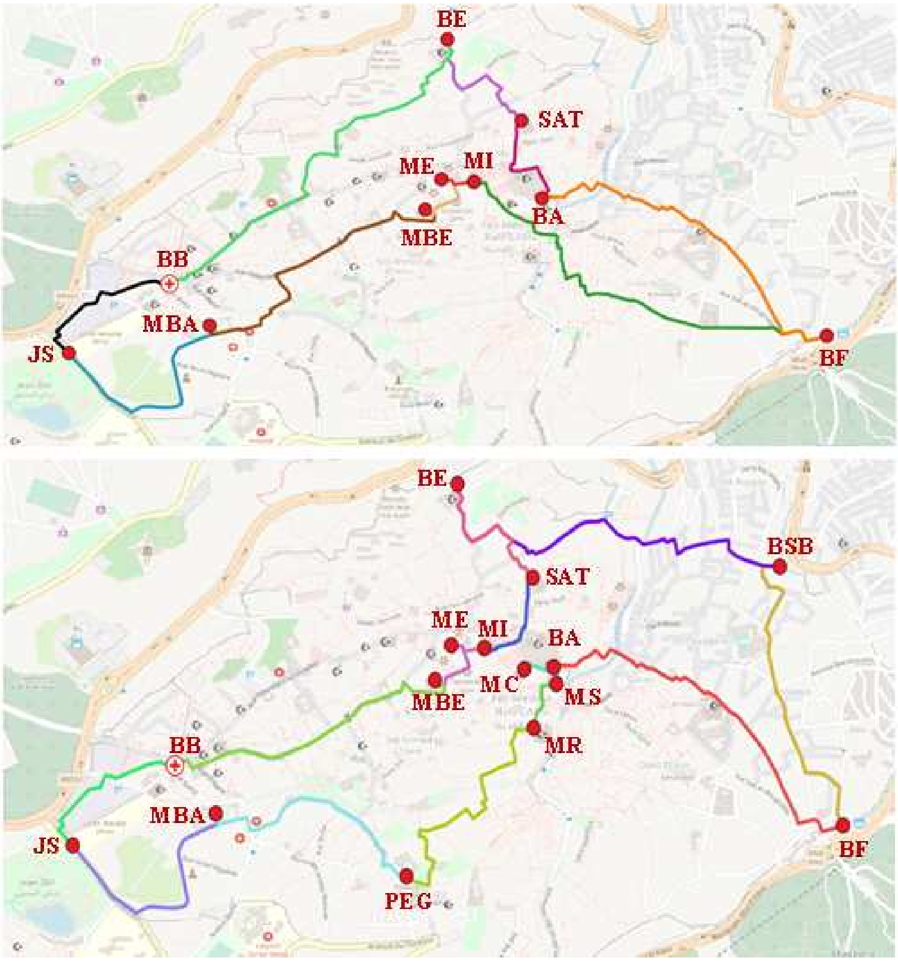

Fig. 3. Itineraries for 10 and 15 POIs.

5. Discussion and conclusion

The current paper essentially aims to provide a new approach to create and suggest optimized routes and circuits, and as a follow-up article, we attempt to overcome the limitations of the approach from our last work [5], which is the high cost in terms of execution time and use cost. The approach to avoid the high cost and improve the poor execution time of the method of Genetic algorithms and Bing Maps API involves trying to go past the use of the API and the A* algorithm alongside the collaborative GIS. The method has an acceptable execution time and overall circuit distance without any cost.

Regarding the perspectives to be expected next, the main one is to include some neural networks, AI, and machine learning modules so that we can efficiently optimize the execution time amid other parameters.

The approach and tests that are being addressed have been centered on improving the routes considering a single criterion, namely, distance. However, in the future, we want to incorporate more constraints into the optimization algorithm. This allows us to design a multi-objective function with various costs rather than merely using distance as the single cost parameter, as earlier approaches realized.

Therefore, combining endeavours in the realm of AI and machine learning with multi-objective optimization will make our solution a solid addition to the new world of smart tourism and provide real benefits to the touristic experience in the city of Fez.

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Appendix

Snapshots of different proposed circuits based on the number of POIs are shown below:

Fig. 4. Itinerary for 5 POIs.

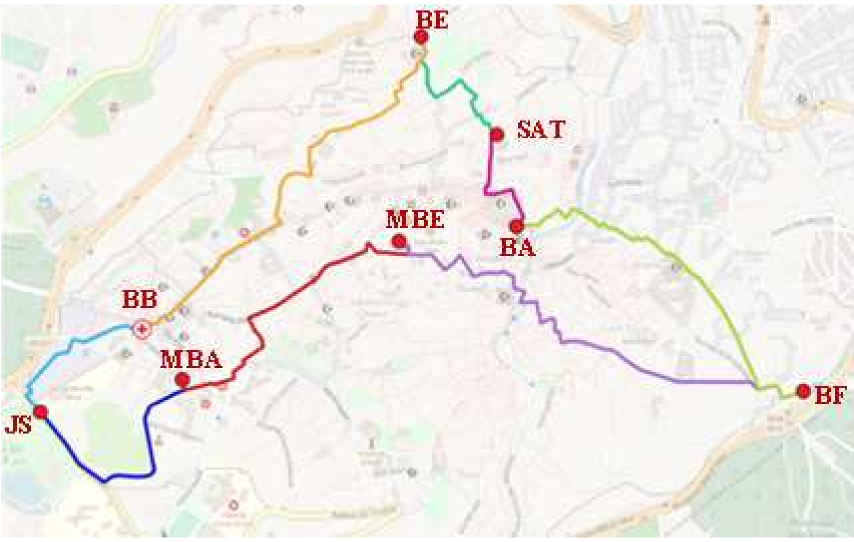

Fig. 5. Itinerary for 8 POIs.

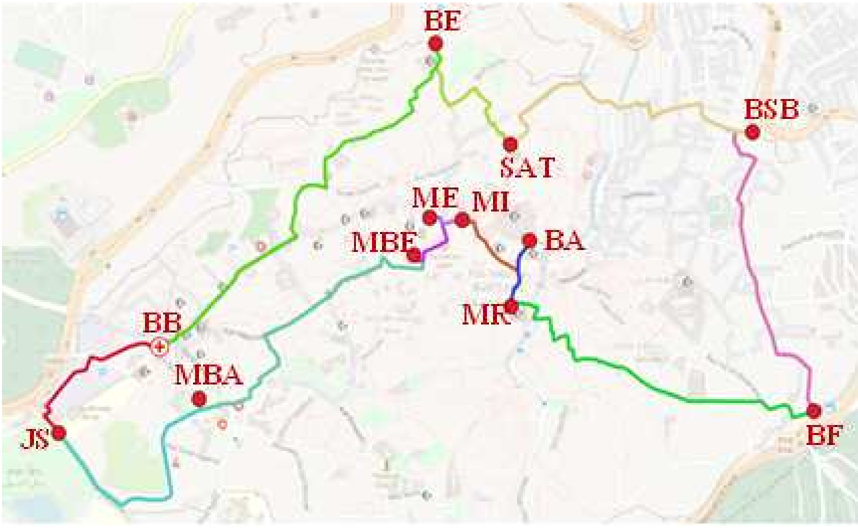

Fig. 6. Itinerary for 12 POIs.

Оптимізація туристичного маршруту за допомогою комбінованого алгоритму A* та генетичного алгоритму

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Ця стаття сприяє оптимізації маршрутів і схем, спрямованих на покращення загального туристичного досвіду відповідно до цілей розумного туризму. Використовуючи передові методи та інструменти, такі як A*, генетичні алгоритми та системи географічної інформації, це дослідження має на меті запропонувати високоефективні шляхи для дослідження міста та відвідування туристичних визначних пам'яток. Він окреслює майбутні прогнози в області інструментів оптимізації, намагаючись інтегрувати технології штучного інтелекту та машинного навчання для створення індивідуальних маршрутів на основі вподобань користувачів. Визнаючи існуючі обмеження в цій області, стаття пропонує нове рішення, що характеризується оптимізованими витратами та скороченим часом виконання. З огляду на те, що основна увага приділяється місту Фес, ця стаття спрямована на вдосконалення інтелектуальних туристичних програм, пропонуючи персоналізований та збагачений досвід.

Ключові слова: *розумний туризм; медоди маршрутизації; оптимізація маршруту; геоінформаційна система (GIS); об'єкт інтересу (POI); A* алгоритм; генетичні алгоритми.*