Enhancing Safety and Multifaceted Preferences to Optimise Cycling Routes for Cyclist-Centric Urban Mobility

Mohammed Alatiyyah
Department of Computer Science, College of Sciences and Humanities-Aflaj,
Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia

***Abstract*—In order to optimise bicycle routes across a variety of multiple parameters, including safety, efficiency and subtle rider preferences, this work explores the difficult domain of the Bike Routing Problem (BRP) using a sophisticated Simulated Annealing approach. In this innovative structure, a wide range of limitations and inclinations are combined and carefully calibrated to create routes that skillfully meet the varied and changing needs of cyclists. Extensive testing on a dataset representing a range of rider preferences demonstrates the effectiveness of this novel approach, resulting in significant improvements in route selection. This research is a significant resource for urban planners and politicians. Its data-driven solutions and strategic recommendations will help them strengthen bicycle infrastructure, even beyond its immediate applicability in resolving the BRP.**

***Keywords*—Bike routing; dynamic vehicle routing inventory routing; approximate dynamic programming**

I. Introduction

When compared to driving, biking is an affordable, environmentally friendly, energy-efficient, and health-conscious alternative to other forms of transportation [1]. It goes beyond simple transportation, providing a means of regular physical activity, encouraging wholesome living, and reducing car emissions. Even with the growing number of towns attempting to develop networks of bicycle lanes, a significant percentage of trips within rideable distances are still made by automobile [2]. Promoting a mentality that embraces riding for recreational and everyday transportation purposes is still a critical obstacle to creating genuinely bike-friendly urban settings.

The key to solving this problem is to carefully hone the bike-path network's functionality and architecture. Riding a bicycle is one of the most effective ways to use energy and promote public health. It is also one of the most important forms of active transportation to reduce traffic congestion and avoid emissions from vehicles. Because walking and cycling are accessible and don't require any specific equipment or expertise, they are suitable for people of all ages and allow them to customise the amount of physical effort they want to put in. But if walking is more suitable for shorter distances, cycling is a better choice for longer ones. However, the belief that riding a bicycle is a dangerous activity endures, mostly because of things like heavy traffic, congested roads, and a lack of designated bike lanes. There are several obstacles that prevent cycling from becoming widely accepted, including worries about comfort, safety, and accessibility [3]. Safety barriers are significant difficulties that arise from concerns about criminal activity, road accidents, or personal injury. Cycling enthusiasts frequently view themselves as vulnerable users of a space designed primarily for motor vehicles. The selection of bike routes is a significantly more complex procedure than the selection of driving routes. Whereas motorists focus on distance and travel time [4], cyclists consider a variety of factors, such as the condition of the bike lanes that are available [5][6] and avoiding hilly terrain and particularly unsettling intersections like roundabouts [7]. Bicyclists' preferred routes are greatly influenced by their closeness to motorised vehicles, especially on high-speed main roads [6]. In order to avoid heavily trafficked or densely populated bike regions, cyclists frequently choose longer but supposedly safer routes [8][9]. This paper introduces a novel approach to the Bike Route Problem (BRP), with a focus on cycling route optimisation to improve safety, efficiency, and compatibility with a range of rider preferences. The new framework synthesises a wide range of limitations and preferences, allowing bicycle routes to be customised to meet the diverse needs of different riders. Our study provides empirical confirmation of the suggested method's effectiveness using a dataset that encompasses a wide range of rider preferences. The flexibility of the Simulated Annealing method demonstrates its ability to create customised routes that meet the various needs of cyclists.

The Bike Route Problem is explained in Section III, while the following sections outline the state of relevant research in Section II. Section IV presents our suggested options for solving the problem, followed by an in-depth analysis of the findings. In the end, Section V summarizes the findings and suggests possible avenues for more research and development.

II. Related Work

Bicycle routing is a problem that has been extensively studied in a number of research paradigms, both directly and indirectly. The multi-objective routing problem was first tackled by Martins et al. [10], who defined the problem in terms of several objective functions and developed a multi-criteria label-setting algorithm for its solution. Later research, like that of Song et al. [11], explored the use of multi-label correction algorithms to find Pareto routes and included hierarchical clustering techniques to expedite the selection procedure. Even with recent improvements in label-setting algorithms, real-time applications are still hindered by the processing timescales these techniques demand.

Routing difficulties have seen the use of evolutionary approaches, most notably genetic algorithms. Genetic algorithms were used in conjunction with High-performance Clusters (HPC) by Arunadevi et al. [12] to address routing issues. Comparably, Kang et al. [13] used evolutionary algorithms to compute segment-specific cost functions in networks of cyclists, taking perceived risk and distance into account. Nevertheless, the multi-objective landscape of bicycle routing was not explored in these research, which mostly concentrated on single-objective optimisation. Several studies have used various criteria to build bicycle routes, frequently maximising each criterion on its own. Using ArcGIS Server and specific Google APIs, Hochmair et al. [14] developed an online cycling route planner. Hrncir et al. [15] used a cost vector that included several parameters such as trip time, comfort, quietness, and levelness with the A-Star algorithm. Chen et al. [16] investigated the use of artificial neural networks to generate routing algorithm heuristic functions. Contraction hierarchies were combined with OpenStreetMap data by Luxen et al. [17] to determine the most straightforward graph-based pathways. Methods for solving the multi-objective bike routing problem have been developed recently, and their effectiveness has been demonstrated in real-world network scenarios. Bike routing algorithms were improved by Hrncir et al. [18] and Hrnvcivr et al. [19], who presented a heuristic-driven Dijkstra algorithm that included a multi-criteria viewpoint. Notable platforms have surfaced in the world of bicycle-specific internet route planners. Though it is available in some areas, Google Maps does not provide much personalization. Using routing techniques like the A* algorithm and contraction hierarchies, OpenTripPlanner incorporates a bicycle planning option that allows users to balance preferences like speed and terrain flatness. Popular in the United Kingdom, Cyclestreets offers a range of route alternatives depending on balance, speed, and tranquilly. Berlin, Germany-based BBBike takes into account variables including the kind of route and the presence of lights. Still, there isn't much written about this topic in the literature. A few studies—Robert et al. [20] and Su et al. [21], for example—introduced computerised cycling route planners customised for certain areas, while Hochmair et al. [14] offered a bicycle route planner for Broward County, Florida, taking into account a variety of factors influenced by cyclist preferences. A route planner for electric bicycles was presented by Tal et al. [22], with an emphasis on weather and energy efficiency.

Although bike routing has progressed, there is still a significant gap in the field of multi-objective methods that balance optimising complicated objectives with computing feasibility. In order to close this gap, this work presents a novel approach that uses genetic algorithms to approximate the optimal Pareto set. It also investigates the possibility of using genetic algorithms to solve multi-objective problems in a reasonable amount of computational time.

III. Bike Routing Problem (BRP)

We define the BRP as follows: let $G = \{V, E\}$ be a undirected weighted graph where, $i \in V$ and $i = 1, 2, \ldots, |V|$ be a set of nodes, and E be a set of edges between nodes where E_{ij} be the edge between V_i and V_j. In addition, each edge has a set attributes denotes A where $a \in A$ and $a = 1, 2, \ldots, |A|$. The starting node is s and the terminal node is e where $s = 1$ and $e = |V|$. However, cyclists have number of constraints. Mandatory Constraints (MC) be denoted MC; $mc \in MC$, where $mc = 1, 2, \ldots, |MC|$. Optional Constraints (OC) be denoted OC; $oc \in OC$, where $oc = 1, 2, \ldots, |OC|$. The total number of constraints $|MC| + |OC| \leq |A|$. In addition, each constraints (MC or OC) be applied in each edge and be denoted MC_{ij}^{mc} or OC_{ij}^{oc} where MC or $OC \subseteq A$.

$$Max \sum_{i=1}^{|V|} \sum_{j=1}^{|V|} A_{ij} \times X_{ij} \tag{1}$$

$$\Big(|MC| + |OC|\Big) \leq |A| \tag{2}$$

$$\sum_{i=1}^{|V|} X_{si} = 1 \tag{3}$$

$$\sum_{i=1}^{|V|} X_{ie} = 1 \tag{4}$$

$$X_{ij} \in \{1, 0\}; \forall i, j = 1, 2, \ldots, |V| \tag{5}$$

$$\sum_{n=1}^{|V|-1} X_{nr} = \sum_{n=2}^{|V|} X_{ru} = 1 \tag{6}$$

$\forall r = 2, \ldots, |V| - 1$

$$2 \leq I_n \leq |V| \tag{7}$$

$\forall n = 2, \ldots, |V|$

$$I_n - I_u + 1 \leq (|V| - 1) \times (1 - X_{nu}) \tag{8}$$

$\forall n, u = 2, \ldots, |V|$

Eq. 1 presents the objective function of BRP where X_{ij} denotes the decision variable moving from node i to node j and the the value of X_{ij} is 0 or 1 (see Eq. (5)). Eq. 3 and 4 represent a constraint to ensure the path starts from s and ends at e. Eq. 6 is a constraint to ensure that the path is connected and each vertex is visited once at most. Eq. 7, I_n denotes the position of node n in the path, and the combination of Eq. 7 and Eq. 8 prevents sub roues.

$$MC_{ij} = \prod_{mc=1}^{|MC|} MC_{ij}^{mc} \tag{9}$$

$$_{ij}^{mc} \in \{1, 0\} \tag{10}$$

$$\forall i, j = 1, 2, \ldots, |V| \text{ and } \forall mc = 1, 2, \ldots, |MC|$$

As have been mentioned above that there are numbers of MCs which is donated in Eq. 9. Mainly, MC_{ij}^{mc} denotes the MC (mc) from node i and j where MC_{ij}^{mc} has one value if the constraint is satisfied, the value is equal 1 otherwise equal 0 (see Eq. (10)).

TABLE I. INSTANCE TEST SCENARIO CATEGORIES

Scenario	Description	Details
S1	Commuter Cyclist	Using bike for work commuting
S2	Fitness Enthusiast	Cycling for exercise and fitness
S3	Urban Explorer	Exploring the city and its surroundings
S4	Nature Lover	Cycling in natural landscapes and parks
S5	Daily Commuter	Regular commuting for work and daily activities
S6	Adventurous Cyclist	Exploring challenging terrains and trails
S7	Family Outings	Cycling with family for recreational activities
S8	Bike Commuters	Using bike for work commuting in a busy city
S9	Night Rider	Cycling during nighttime for relaxation
S10	Touring Cyclist	Long-distance touring and exploration

$$OC_{ij} = \frac{\sum_{oc=1}^{|OC|} OC_{ij}^{oc}}{|OC|} \tag{11}$$

$$0 \leq OC_{ij}^{oc} \leq 1 \tag{12}$$

$$\forall i, j = 1, 2, \ldots, |N| \text{ and } \forall oc = 1, 2, \ldots, |OC|$$

In contrast, a OC indicates a specific level of satisfaction and meeting it is optional. Numbers of OCs which is donated in Eq. 11, where OC_{ij}^{oc} one value between 0 to 1 (see Eq. (12)). In additional, Eq. 13 presents the calculation of MC and OC from i to j.

$$A_{ij} = MC_{ij} \times OC_{ij} \tag{13}$$

IV. SOLUTION APPROACHES

In this section, we elaborate on our heuristic-driven Simulated Annealing method designed for solving the BRP. Our approach integrates a data model for constraints and Simulated Annealing techniques to address the Bike Route Problem. The fundamental concept involves simplifying the complexity of the problem by consolidating constraints into a single value that encapsulates the attributes sought by riders.

A. Benchmark Instances

To the best author knowledge there is not any dataset for bike routing problem, so A set of benchmark instances were created to analyze how the propose model performs through numerical experiment results. Random problem instances were generated so as to maintain the properties of one of ten general scenario categories as defined in Table I. In each scenario, it has been generated different circumstances where difference constraints and preferences are applied. Each instance was randomly generated assuming a grid of 40 by 40 miles based on an area similar in size Newcastle upon Tyne, UK. Table II shows the details of each scenario, and in the dataset has been created five attributes for each of edges.

Table II delineates a variety of constraints and preferences. The Optional Constraints (OC) column details the preferences of the riders, while the Mandatory Constraints (MC) column lists the constraints that are requisite. Furthermore, the Traffic Volume attribute accommodates varying preferences: certain riders opt for routes with low traffic, whereas others may favor routes with moderate traffic levels. Additionally, the Elevation attribute reflects diverse inclinations regarding physical exertion; some riders seek routes with minimal elevation to reduce effort, while others pursue routes with significant elevation for a more challenging ride.

TABLE II. INSTANCE TEST SCENARIO IN MORE DETAILS

Scenario	Attributes				
	Safety	Bike Lanes	Traffic Volume	Scenery	Elevation
S1	MC	OC	OC (M)	OC	OC (Low)
S2	OC	OC	OC (L)	MC	MC
S3	OC	OC	OC (M)	MC	OC (Low)
S4	MC	OC	OC (L)	MC	OC (Low)
S5	MC	MC	OC (L)	OC	OC (Low)
S6	OC	OC	OC (L)	OC	OC (High)
S7	MC	OC	OC (L)	OC	OC (Low)
S8	OC	OC	MC	OC	OC (Low)
S9	OC	OC	OC (L)	OC	OC (Low)
S10	MC	OC	OC (L)	OC	OC (High)

TABLE III. INSTANCE SCENARIO WITH START AND END LOCATION

Instance	Start location	End location
I1	121	165
I2	77	351
I3	462	145
I4	282	393
I5	25	115
I6	80	476
I7	323	342
I8	109	464
I9	491	171
I10	31	375

The ten benchmark sets under consideration encompass a total of 100 instances, with each set comprising 10 instances characterized by a node count of 500. While each benchmark (scenario) shares identical start and end points, they are differentiated by their unique constraints and preferences. Table III details the start and end points for each instance, providing a clear reference for the scenarios tested.

Algorithm 1 Bike Routing Problem

$SenarioData \leftarrow ReadingDataFiles()$
$Edges \leftarrow ReadingEdges()$
while $i <= SenarioData.lenth()$ **do**
  while $j <= Edges.lenth()$ **do**
    $InitialRoute \leftarrow CreateInitialRoute()$
    $InitialTemperature = 1000$
    $CoolingRate = 0.995$
    $BestRoute = SimulatedAnnealing()$
    $j \leftarrow j + 1$
  end while
  $i \leftarrow i + 1$
end while

B. Simulated Annealing

Simulated Annealing (SA) is a powerful optimization algorithm inspired by the annealing process in metallurgy. Initially introduced by Kirkpatrick, Gelatt, and Vecchi in the 1980s [23], SA mimics the annealing of materials, where a solid is heated to high temperatures and then gradually cooled to minimize its energy state. This process allows the algorithm to escape local optima and explore the solution space more effectively. The key idea behind SA is to accept worse solutions

Algorithm 2 $SimulatedAnnealing$ Algorithm

while $temperature > 0.1$ **do**
  while $ReplacedNode$ **do**
    $SwapIndex \leftarrow random(1, Route.length())$
    $NewNode \leftarrow FindReplacedNode()$
    if $NewNode! = Null$ **then**
      $Route[SwapIndex] \leftarrow NewNode$
      $Update =$
    else
      $ReplacedNode \leftarrow False$
    end if
  end while
end while

TABLE IV. THE RESULT FOR INSTANCE 1

scenario	Total Scores	Path
Scenario-1	[121, 297, 422, 165]	0.92
Scenario-2	[121, 297, 346, 165]	0.81
Scenario-3	[121, 297, 346, 165]	0.68
Scenario-4	[121, 319, 309, 165]	0.82
Scenario-5	[121, 297, 422, 165]	1.00
Scenario-6	[121, 319, 309, 165]	0.33
Scenario-7	[121, 297, 143, 165]	0.59
Scenario-8	[121, 297, 422, 165]	0.84
Scenario-9	[121, 239, 257, 249, 165]	0.35
Scenario-10	[121, 297, 143, 165]	0.51

TABLE V. THE RESULT FOR INSTANCE 2

Scenario	Total Scores	Path
Scenario-1	[77, 422, 351]	0.33
Scenario-2	[77, 422, 351]	0.78
Scenario-3	[77, 422, 351]	0.33
Scenario-4	[77, 422, 351]	0.50
Scenario-5	[77, 422, 351]	0.55
Scenario-6	[77, 422, 351]	0.28
Scenario-7	[77, 422, 351]	0.35
Scenario-8	[77, 422, 351]	1.00
Scenario-9	[77, 422, 351]	0.20
Scenario-10	[77, 422, 351]	0.43

TABLE VI. THE RESULT FOR INSTANCE 3

Instance	Total Scores	Path
Scenario-1	[462, 86, 145]	0.83
Scenario-2	[462, 86, 145]	1.00
Scenario-3	[462, 41, 2, 145]	0.63
Scenario-4	[462, 86, 145]	1.00
Scenario-5	[462, 86, 145]	0.93
Scenario-6	[462, 86, 145]	0.46
Scenario-7	[462, 86, 145]	0.83
Scenario-8	[462, 86, 145]	0.61
Scenario-9	[462, 86, 145]	0.56
Scenario-10	[462, 86, 145]	0.76

TABLE VII. THE RESULT FOR INSTANCE 4

Instance	Total Scores	Path
Scenario-1	[282, 291, 148, 393]	0.57
Scenario-2	[282, 291, 243, 393]	0.83
Scenario-3	[282, 366, 144, 393]	0.50
Scenario-4	[282, 366, 144, 393]	0.60
Scenario-5	[282, 291, 243, 393]	0.61
Scenario-6	[282, 455, 325, 393]	0.26
Scenario-7	[282, 291, 243, 393]	0.41
Scenario-8	[282, 291, 243, 393]	0.82
Scenario-9	[282, 455, 325, 393]	0.23
Scenario-10	[282, 291, 243, 393]	0.49

with a certain probability, enabling the algorithm to explore the solution space broadly before converging towards the optimal solution [23][24]. This approach has proven to be highly effective in solving complex optimization problems where the objective function is not explicitly defined and can only be evaluated through computationally expensive simulations [24]. SA's ability to balance exploration and exploitation makes it a popular choice in various real-world applications, ranging from engineering and logistics to machine learning and artificial intelligence [24]. Its widespread applicability and efficiency in tackling challenging optimization problems have solidified its position as a prominent metaheuristic algorithm in the field of computational optimization.

V. COMPUTATIONAL RESULTS

In this section, we provide the outcomes of our numerical experiments. Initially, we assess the efficiency of our BRP formulation as well as the Constraints formulation coupled with Simulated Annealing. Subsequently, we analyze the performance of our proposed Simulated Annealing algorithm. All experiments were carried out on a computer with an Intel i7-2.10 GHz processor and 64 GB RAM, running on the Windows 11-x64 operating system.

The study examined the effectiveness of BRP in uneven situations. Results from the tenth series of tests were analyzed in comparison with outcomes obtained using Simulated Annealing methods. Tables IV - XIII summarize the computational results for each instance, respectively. In these tables, the three columns display the scenario name, total scores based on the edges are visited, and the path. The total scores values are evaluated based in Eq. 1. Please note that, the computation times of these heuristics are less than 1s.

Table IV reports the results obtained from the test problem in instance-1 which representing a scenario of transporting from Node-121 to Node-165. As it can be seen, the results can be categorized into five categories: (1) Scenario 1, 5, and 8, (2) Scenario 2 and 3, (3) Scenario 4 and 6, (4) Scenario 7 and 10, and (5) Scenario 9; each one of these category has the same result.

Table V presents the results of the instance-2 which presents the problem of moving from Node-77 to Node-351. In addition, Table XII presents the results of the instance-9 which presents the problem of moving from Node-491 to Node-171. Surprisingly, all results from different scenarios has the same result (path); In instance-2 the result is [77, 422, 351], and the instance-9 the result is [491, 218, 171].

Table VI shows the results of the instance-3 which presents the problem of moving from Node-462 to Node-145. In this experiment, All scenarios shows the same results (path) except the scenario-3.

Table VII presents the results of the instance-3 which presents the problem of moving from Node-282 to Node-393. The results can be seen in four categories: (1) Scenario 2, 5, 7, 8, and 10, (2) Scenario 3 and 4, (3) Scenario 6 and 9, and (4) Scenario 1.

Table VIII presents the results of the instance-2 which presents the problem of moving from Node-25 to Node-115. There are six scenarios have different result completely which

TABLE VIII. THE RESULT FOR INSTANCE 5

Instance	Total Scores	Path
Scenario-1	[25, 240, 184, 115]	0.56
Scenario-2	[25, 18, 108, 115]	1.00
Scenario-3	[25, 497, 131, 115]	0.47
Scenario-4	[25, 117, 285, 115]	0.72
Scenario-5	[25, 18, 108, 115]	0.95
Scenario-6	[25, 383, 46, 115]	0.49
Scenario-7	[25, 75, 110, 115]	0.60
Scenario-8	[25, 240, 184, 115]	0.70
Scenario-9	[25, 462, 378, 285, 115]	0.41
Scenario-10	[25, 281, 170, 454, 115]	0.49

TABLE IX. THE RESULT FOR INSTANCE 6

Instance	Total Scores	Path
Scenario-1	[80, 404, 476]	0.74
Scenario-2	[80, 404, 476]	0.91
Scenario-3	[80, 404, 476]	0.52
Scenario-4	[80, 404, 476]	0.83
Scenario-5	[80, 404, 476]	0.87
Scenario-6	[80, 404, 476]	0.42
Scenario-7	[80, 40, 166, 476]	0.46
Scenario-8	[80, 404, 476]	1.00
Scenario-9	[80, 404, 476]	0.42
Scenario-10	[80, 404, 476]	0.70

TABLE X. THE RESULT FOR INSTANCE 7

Instance	Total Scores	Path
Scenario-1	[323, 421, 342]	0.56
Scenario-2	[323, 421, 342]	0.67
Scenario-3	[323, 421, 342]	0.56
Scenario-4	[323, 421, 342]	0.61
Scenario-5	[323, 421, 342]	0.67
Scenario-6	[323, 437, 313, 342]	0.38
Scenario-7	[323, 421, 342]	0.58
Scenario-8	[323, 421, 342]	0.67
Scenario-9	[323, 421, 342]	0.31
Scenario-10	[323, 421, 342]	0.53

TABLE XI. THE RESULT FOR INSTANCE 8

Instance	Total Scores	Path
Scenario-1	[109, 18, 100, 464]	0.68
Scenario-2	[109, 106, 498, 464]	0.77
Scenario-3	[109, 125, 377, 464]	0.49
Scenario-4	[109, 370, 243, 464]	0.83
Scenario-5	[109, 225, 214, 464]	0.90
Scenario-6	[109, 341, 498, 464]	0.32
Scenario-7	[109, 432, 377, 464]	0.67
Scenario-8	[109, 370, 202, 464]	0.64
Scenario-9	[109, 20, 458, 268, 464]	0.38
Scenario-10	[109, 252, 56, 464]	0.79

TABLE XII. THE RESULT FOR INSTANCE 9

Instance	Total Scores	Path
Scenario-1	[491, 218, 171]	0.64
Scenario-2	[491, 218, 171]	0.92
Scenario-3	[491, 218, 171]	0.84
Scenario-4	[491, 218, 171]	0.90
Scenario-5	[491, 218, 171]	1.00
Scenario-6	[491, 218, 171]	0.59
Scenario-7	[491, 218, 171]	0.63
Scenario-8	[491, 218, 171]	0.80
Scenario-9	[491, 218, 171]	0.47
Scenario-10	[491, 218, 171]	0.75

TABLE XIII. THE RESULT FOR INSTANCE 10

Instance	Total Scores	Path
Scenario-1	[31, 356, 375]	1.00
Scenario-2	[31, 356, 375]	0.95
Scenario-3	[31, 356, 375]	0.88
Scenario-4	[31, 356, 375]	1.00
Scenario-5	[31, 336, 26, 375]	0.60
Scenario-6	[31, 356, 375]	0.62
Scenario-7	[31, 356, 375]	1.00
Scenario-8	[31, 356, 375]	0.63
Scenario-9	[31, 336, 26, 375]	0.24
Scenario-10	[31, 356, 375]	1.00

are Scenario 3, 4, 6, 7, 9, and 10. However, Scenarios 1 and 8 are the same, and the Scenario 2 and 5 are the same.

Table IX shows the results of the instance-6 which presents the problem of moving from Node-80 to Node-476. In this experiment, All scenarios shows the same results (path) except the scenario-7. Moreover, Table X shows the results of the instance-7 which presents the problem of moving from Node-323 to Node-342. Also, ins this experiment, All scenarios shows the same results (path) except the scenario-6.

Table XI shows the results of the instance-8 which presents the problem of moving from Node-109 to Node-464. Surprisingly, all results are different for each scenario.

Table XIII presents the results of the instance-10 which presents the problem of moving from Node-31 to Node-375. The results can be seen in two categories: (1) Scenario 1, 2, 3, 4, 6, 7, 8 and 10, and (2) Scenario 5 and 9.

VI. CONCLUSIONS AND FUTURE WORK

The study successfully applied a heuristic-driven Simulated Annealing algorithm to the BRP, demonstrating its efficacy in processing and optimizing complex routing problems within reasonable computational times. The results confirmed that the proposed method could handle a variety of scenarios by accommodating diverse constraints and preferences, thus offering a flexible and robust solution to the BRP. The findings suggest that the method is not only applicable in the context of cycling but may also extend to other forms of transportation where route optimization is essential. The research contributes to the field by providing a systematic approach to addressing BRP and paving the way for more sustainable urban transport systems. Future research directions include scaling the proposed solution to larger datasets and urban areas with more complex networks. There is also scope for integrating real-time data, such as traffic updates and weather conditions, to enhance the dynamicity and responsiveness of the route planning process. Another avenue for exploration is the application of the Simulated Annealing approach to different types of multi-objective routing problems beyond cycling, such as pedestrian pathfinding and electric vehicle charging station routes. Further studies could also investigate the integration of machine learning techniques to predict and adapt to cyclists' preferences more accurately.

REFERENCES

[1] S. Ryu, A. Chen, J. Su, and K. Choi, "Two-stage bicycle traffic assignment model," *Journal of Transportation Engineering, Part A: Systems*, vol. 144, no. 2, p. 04017079, 2018.

[2] B. E. Saelens, J. F. Sallis, and L. D. Frank, "Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures," *Annals of behavioral medicine*, vol. 25, no. 2, pp. 80–91, 2003.

[3] D. Piatkowski, R. Bronson, W. Marshall, and K. J. Krizek, "Measuring the impacts of bike-to-work day events and identifying barriers to increased commuter cycling," *Journal of Urban Planning and Development*, vol. 141, no. 4, p. 04014034, 2015.

[4] J. P. Schmitt and F. Baldo, "A method to suggest alternative routes based on analysis of automobiles' trajectories," in *2018 XLIV Latin American Computer Conference (CLEI)*. IEEE, 2018, pp. 436–444.

[5] J. Pucher and R. Buehler, "Making cycling irresistible: lessons from the netherlands, denmark and germany," *Transport reviews*, vol. 28, no. 4, pp. 495–528, 2008.

[6] R. Buehler and J. Dill, "Bikeway networks: A review of effects on cycling," *Transport reviews*, vol. 36, no. 1, pp. 9–27, 2016.

[7] M. Rasanen and H. Summala, "Car drivers' adjustments to cyclists at roundabouts," *Transportation Human Factors*, vol. 2, no. 1, pp. 1–17, 2000.

[8] N. Y. Tilahun, D. M. Levinson, and K. J. Krizek, "Trails, lanes, or traffic: Valuing bicycle facilities with an adaptive stated preference survey," *Transportation Research Part A: Policy and Practice*, vol. 41, no. 4, pp. 287–301, 2007.

[9] S. E. Vedel, J. B. Jacobsen, and H. Skov-Petersen, "Bicyclists' preferences for route characteristics and crowding in copenhagen–a choice experiment study of commuters," *Transportation Research Part A: Policy and Practice*, vol. 100, pp. 53–64, 2017.

[10] E. Q. V. Martins, "On a multicriteria shortest path problem," *European Journal of Operational Research*, vol. 16, no. 2, pp. 236–245, 1984.

[11] Q. Song, P. Zilecky, M. Jakob, and J. Hrncir, "Exploring pareto routes in multi-criteria urban bicycle routing," in *17th international IEEE conference on intelligent transportation systems (ITSC)*. IEEE, 2014, pp. 1781–1787.

[12] J. Arunadevi, A. Johnsanjeevkumar, and N. Sujatha, "Intelligent transport route planning using parallel genetic algorithms and mpi in high performance computing cluster," in *15th International Conference on Advanced Computing and Communications (ADCOM 2007)*. IEEE, 2007, pp. 578–583.

[13] L. Kang and J. D. Fricker, "Bicycle-route choice model incorporating distance and perceived risk," *Journal of Urban Planning and Development*, vol. 144, no. 4, p. 04018041, 2018.

[14] H. Hochmair and F. Zhaohui, "Web based bicycle trip planning for broward county, florida. gis center," 2013.

[15] J. Hrncir, Q. Song, P. Zilecky, M. Nemet, and M. Jakob, "Bicycle route planning with route choice preferences," in *ECAI 2014*. IOS Press, 2014, pp. 1149–1154.

[16] H.-C. Chen and J.-D. Wei, "Using neural networks for evaluation in heuristic search algorithm," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 25, no. 1, 2011, pp. 1768–1769.

[17] D. Luxen and C. Vetter, "Real-time routing with openstreetmap data," in *Proceedings of the 19th ACM SIGSPATIAL international conference on advances in geographic information systems*, 2011, pp. 513–516.

[18] J. Hrncir, P. Zilecky, Q. Song, and M. Jakob, "Speedups for multi-criteria urban bicycle routing," in *15th Workshop on Algorithmic Approaches for Transportation Modelling, Optimization, and Systems (ATMOS 2015)*. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2015.

[19] J. Hrnčíř, P. Žileckỳ, Q. Song, and M. Jakob, "Practical multicriteria urban bicycle routing," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 3, pp. 493–504, 2016.

[20] R. J. Turverey, D. D. Cheng, O. N. Blair, J. T. Roth, G. M. Lamp, and R. Cogill, "Charlottesville bike route planner," in *2010 IEEE Systems and Information Engineering Design Symposium*. IEEE, 2010, pp. 68–72.

[21] J. G. Su, M. Winters, M. Nunes, and M. Brauer, "Designing a route planner to facilitate and promote cycling in metro vancouver, canada," *Transportation research part A: policy and practice*, vol. 44, no. 7, pp. 495–505, 2010.

[22] I. Tal, A. Olaru, and G.-M. Muntean, "ewarpe-energy-efficient weather-aware route planner for electric bicycles," in *2013 21st IEEE International Conference on Network Protocols (ICNP)*. IEEE, 2013, pp. 1–6.

[23] S. Kirkpatrick, C. D. Gelatt Jr, and M. P. Vecchi, "Optimization by simulated annealing," *science*, vol. 220, no. 4598, pp. 671–680, 1983.

[24] L. Ingber, "Adaptive simulated annealing (asa): Lessons learned," *arXiv preprint cs/0001018*, 2000.