MODyPer: Multi-Objective Dynamic Personalized Route Planning for Vulnerable Road Users

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Abstract

Urban mobility is increasingly shifting towards sustainable modes of transportation, such as walking and cycling, necessitating intelligent route planning systems that cater to dynamic user preferences. This paper introduces MODyPer, a novel graph-based framework designed to optimize route recommendations for vulnerable road users (i.e., pedestrians and cyclists) by integrating multiple objectives, including travel distance, comfort, and environmental criteria. Unlike existing systems that prioritize single objectives (e.g., shortest path), our framework incorporates personalized weighting mechanisms, allowing users to define their preferences dynamically. We applied MODyPer to two real-world urban scenarios of Italian cities, demonstrating its effectiveness in balancing competing objectives while providing timely, user-centric routing.

CCS Concepts

• **Applied computing** → *Multi-criterion optimization and decision-making*; • **Information systems** → **Information systems applications**.

Keywords

Route planning, Personalized routing, Smart mobility

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1 Introduction

Urban sustainability imperatives are driving a global transition to non-motorized transportation, with walking and cycling as key pillars of greener mobility. This transition relies on addressing critical barriers faced by vulnerable road users (VRUs), namely pedestrians and cyclists, whose adoption of active transportation modes is often hampered by infrastructure gaps and negative perceptions of the built environment. Studies reveal that VRUs actively avoid routes perceived as dangerous, unsafe, polluted, or psychologically stressful, undermining sustainability goals [1, 11].

Conventional routing systems exacerbate this challenge by prioritizing singular objectives like shortest distance [6, 18], ignoring multifaceted trade-offs between safety risks [12], health problems [11], comfort deficits [1]. To fully realize the potential of sustainable mobility, a personalized route planning for VRUs in urban contexts is essential [7]. This involves creating customized navigation solutions that address the needs of individuals. Previous works exhibit limitations in personalization flexibility and MOO. For example, CAPRIO [5] includes environmental criteria (e.g., minimizing outdoor exposure) but remains constrained to single-objective formulations. Commercial tools (e.g., Google Maps, OsmAnd) provide limited personalization in pedestrian/cyclist routing. BRouter[1] enables cyclist-specific adjustments (e.g., slope avoidance) but lacks integration of safety or air quality metrics. Most MOO research focuses on vehicular logistics. Common approaches include *weighted aggregation* [15, 16] to combine objectives linearly but scale poorly beyond two criteria, or *constraint-based methods* [10, 19] to optimize one objective while bounding others, limiting Pareto front exploration, or *evolutionary algorithms* [4, 22] that employ genetic/particle-swarm optimization for complex objectives but incur high computational overhead unsuitable for real-time routing, or *Pareto front analysis* [12, 21] to identify non-dominated solutions but becomes intractable for large networks if no optimization strategy is used. Limited studies address preference-based weighting in MOO [3, 13, 23] but none support dynamic weight adjustments during navigation or address pedestrian/cyclist-specific objectives (e.g., sidewalk safety).

In this paper, we present MODyPer[2], a multi-objective graph-based framework. By integrating time-dependent variables (air quality) and static factors (green areas, infrastructure quality), MODyPer generates Pareto-optimal routes balancing distance, infrastructure comfort, and environmental quality. Validated in Italian urban landscapes, our framework allows VRUs to navigate cities sustainably. This work is part of the AIQS project [17] that aims to improve the accuracy of air quality sensors using artificial intelligence and to enable pollution-aware pedestrian routing for healthier urban mobility.

2 Methodology

Our goal is to provide comfortable routes for VRUs in an urban area. First, we analyze the effective criteria that can influence routing choices [1, 11, 14], distinguishing qualitative characteristics like environmental conditions (noise levels, air quality indices) and

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[1] https://brouter.de

[2] The source code is available at https://github.com/federicarollo/GRAFMOVE/tree/main/MODyPer. The framework was implemented using Python and Neo4j on a laptop powered by 32GB RAM and 14 processors with Intel(R) Core(TM) Ultra 7 155U CPU, 1700 Mhz, setting Neo4j JVM heap max size to 1G.

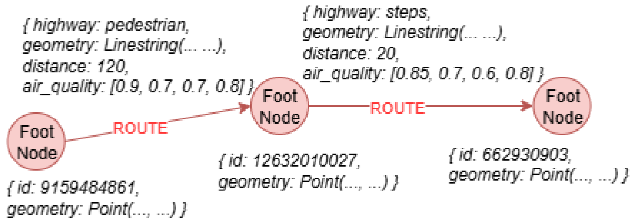

Figure 1: Example of ROUTE relationships.

traffic dynamics (traffic volume, waiting time at intersections) and quantitative characteristics such as pavement materials, presence of sidewalk. Thus, we implement a framework capable of handling and integrating big spatial and heterogeneous data in a graph-based data modeling. The framework calculates numerous candidate paths and finds the solutions in the Pareto front. Based on user preferences, the best route is chosen among this set of solutions.

2.1 Graph modeling

Following the structure of OSM and our approach proposed in [20], we create a directed graph where nodes represent OSM-defined junctions or road shape points, with properties such as *OSM identifier* and *GPS coordinates* in the Well-known text (WKT) format, and edges correspond to roads, with properties including *geometry* representing the shape of the road as Linestring, *distance*, i.e., the geometric length of the road, *highway*, i.e., the type of roads. Nodes are labeled as `RouteNode` and edges as `ROUTE`. The direction of the edge indicates the permitted travel direction. Based on the highway OSM attribute, nodes permitting pedestrian and cycling access are labeled as `FootNode` and `BikeNode`, respectively.

Each edge in the graph is assigned multiple weights, which are described in detail below and can be used for routing computations. Among these weights, some are time-invariant (e.g., the length of the road segment), while others are time-dependent (e.g., air quality) and utilize the Attributes Time Aggregated Graph (ATAG) structure [9], which allows to store multiple weights in different time slots, e.g., rush hours, early morning, or late night. An example is shown in Figure 1.

Road classification. The quality and type of infrastructure, such as the presence of dedicated lanes, segregation from motorized traffic, and pavement conditions, play a crucial role in route choice, especially in terms of safety and comfort for non-motorized users. Based on OSM guidelines for pedestrians[3] and cyclists[4], we define five classes of road segments, from highest priority (Class 1 - dedicated pedestrian and fully segregated cycling infrastructures) to lowest priority (Class 5 - roads with high-speed traffic (>50 Km/h) where pedestrians and cyclists are permitted).

Green area inclusion. Based on OSM representation of green areas and the approach proposed in [20], each edge is assigned a new property, allowing consideration of green space proximity in routing, calculated as follows:

$$\text{green\_area\_weight} = \text{distance} \times \left(1 + \frac{\text{green\_area}}{100}\right)^{-1}$$

where *distance* is the edge length and *green_area* is equal to 100 if both the source and target nodes of the edge are in a green area, 50 if only one, and 0 otherwise.

Air quality assessment Given point-referenced air quality measurements (e.g., NO_2 or $PM_{2.5}$ concentrations) from monitoring stations or sensors, spatial interpolation is required to estimate pollution levels across the entire geographic area. The resulting continuous pollution surface enables derivation of representative air quality values along road segments. After applying the anisotropic Inverse Distance Weighting (IDW) technique for interpolation using GDAL[5], we define a set of square buffers around N equally-spaced points on each edge and compute the pollution exposure:

$$AQ_m = \frac{1}{|B|} \sum_{b \in B} \frac{1}{P^2} \sum_{p \in b} AQ_p \times \text{distance}$$

where B is the set of buffers ($|B| = N + 2$), $b \in B$, P is the size in pixel of the buffer, and AQ_p is the pollutant value at pixel p. This formulation captures cumulative exposure by weighting the mean concentration by edge length.

2.2 Best route selection

The route selection problem is formulated as a Pareto MOO task. Given two nodes in a finite graph, there exists a finite set of simple paths (i.e., cycle-free paths) connecting them. We create a set of candidate paths, identify the Pareto front and select the optimal route based on user preferences. The Pareto front comprises all non-dominated solutions: a solution is considered non-dominated if no other solution exists that improves all objectives simultaneously. To approximate the Pareto front effectively, a diverse set of candidate paths is needed. Since generating all possible paths is computationally infeasible, the approach begins with paths that individually optimize each objective and expands the set using additional paths derived from minimizing a fictitious cost function. Candidate solutions are processed using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [8] through pymoo [2]. Then, there are three options for route selection: (1) *user-defined importance weights* associated to each objective that allows to define a point in the normalized objective space and identify the closest point in the Pareto front and the corresponding solution, i.e., the route that best suits user needs, (2) *user-defined importance weights and constraints* to set objectives' thresholds, (3) *optimal trade-off* defined as the point closest to the origin of the Pareto front in the normalized objective space, representing the most balanced compromise solution that best satisfies all competing objectives.

3 Case studies

To verify the methodology in a real-world routing problem, we selected two medium-size Italian cities: Modena and Ferrara. The creation of each graph required less than 1 minute; key statistics are shown in Table 1. Based on the available data in each city, we tested different scenarios.

For **Modena** we use the length of the road, the classification of the road, and the location of the green areas as objectives for the best route identification. To evaluate our approach, we randomly sampled 50 `FootNode` pairs with Euclidean distances ranging from

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[3] https://wiki.openstreetmap.org/wiki/Guidelines_for_pedestrian_navigation
[4] https://wiki.openstreetmap.org/wiki/Bicycle
[5] https://gdal.org/

Table 1: Key statistics of exemplar graphs.

	Ferrara	Modena
Area (Km^2)	100	100
Pedestrian- and cyclist-accessible pathway in green areas (Km)	300	200
`RouteNode`	42374	46507
`FootNode` / `BikeNode`	34661	40523
`Route`	79876	94917

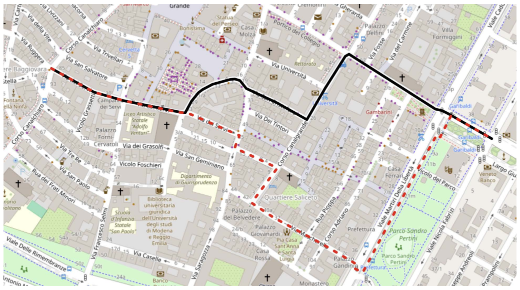


Figure 2: Two alternative routes in Modena: the shortest path (black solid line) and the more comfortable (red dashed line).

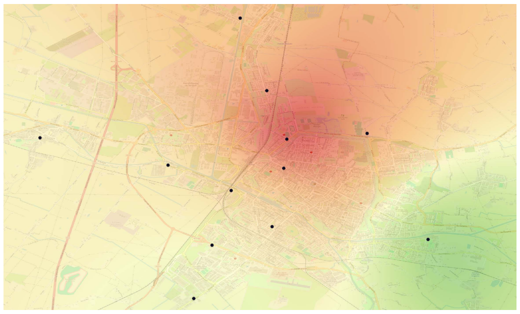
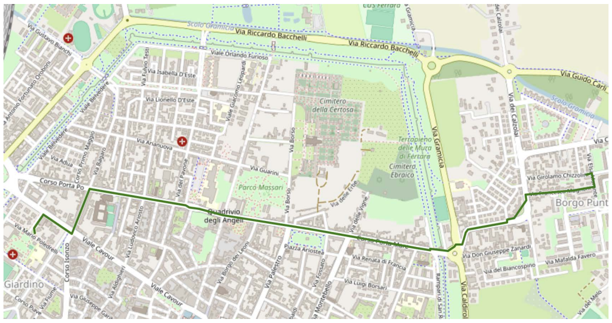
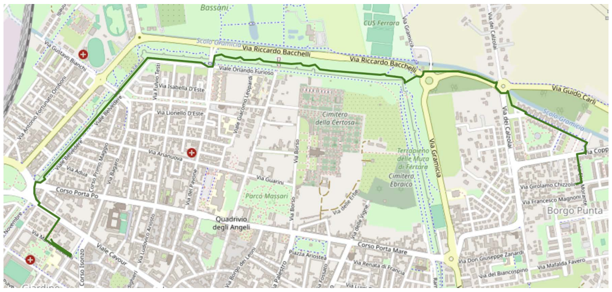


Figure 3: $PM_{2.5}$ concentrations in Ferrara on June 11, 2025, at 6:00 a.m.

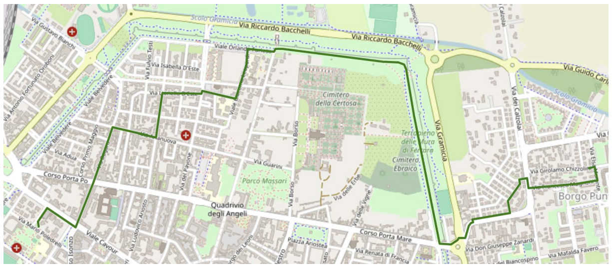
500 meters to 3 Km, ensuring comprehensive testing across varying urban route scales. Selecting randomly the time interval (night, morning, afternoon and evening), for each pair, we generated 1,000 candidate paths and computed the Pareto front. We compared solutions that optimize a single objective with the solution that represents the best trade-off among the three objectives in the Pareto front. The same comparison was performed on a randomly selected set of 50 `BikeNode` nodes. The generation of candidate paths required approximately 40 seconds of computation time; while the Pareto front was computed in an average of 1 minute and reached a mean hypervolume of 1.3 on the normalized Pareto front, confirming the effectiveness of the candidate path generation process and a comprehensive coverage of the solution space. Our analysis reveals that, compared to the shortest path, the optimal trade-off route entails, on average, an increase of 20% in path length and an increase of 12% in the presence of green spaces.



(a) Shortest, least polluted and best tradeoff.



(b) Path near green areas



(c) Path optimizing road priority

Figure 4: Different paths based on different objectives in Ferrara: distance, $PM_{2.5}$, green proximity and road priority.

An example is illustrated in Figure 2, which depicts two possible cycling routes between Palazzo Malmusi and Largo Giuseppe Garibaldi. The black line shows the route optimized solely for distance (without additional criteria), representing the shortest possible path; while the red dashed line shows the route optimized for three criteria: distance (user-defined weight = 0.3), road classification priority (0.2), and proximity to green areas (0.5). Even if the second solution exceeds the first solution by approximately 300 meters in length, it provides improved cyclist comfort prioritizing the bike lane that runs through the park.

In **Ferrara**, as part of the European Air-Break project, the municipality collects and publishes hourly $PM_{2.5}$ and PM_{10} measurements from 12 monitoring stations.[6] PM concentrations exhibit significant daily variability. Figure 3 shows interpolated $PM_{2.5}$ heatmaps on June 11, 2025 at 6:00 p.m., with sensor locations marked by black dots. The red color indicates high pollution levels (46 $\mu g\, m^{-3}$), while

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[6] Data are publicly available on the municipal open-data portal: https://dati.comune.fe.it/dataset.

green reflects lower concentrations ($11\,\mu\mathrm{g\,m^{-3}}$). The contrast between different areas in the map highlights the spatial heterogeneity of air pollution. The same experiment conducted for Modena was replicated for Ferrara by randomly selecting 50 `FootNode` pairs and 50 `BikeNode` pairs and considering $\mathrm{PM}_{2.5}$ interpolated data of June, 11 2025 (the reference time has been randomly selected each time), in addition to road length, road classification and the location of green areas. The averaged hypervolume is 1.35. The route with the optimal trade-off in most cases corresponds to the least polluted path. Figure 4 illustrates three different paths at 6 a.m. from Parco Mirco Ferrari to Piazzale Broni. When evaluating all four predefined objectives, the route offering the optimal tradeoff aligns with the shortest and least polluted path.

4 Conclusions

This paper introduced MODyPer, a multi-objective dynamic routing framework designed to enhance active mobility (walking/cycling) in urban environments by optimizing routes across distance, infrastructure comfort, and environmental quality. Our graph-based approach, validated through real-world applications in Modena and Ferrara, Italy, demonstrates that personalized multi-criteria routing increases path attractiveness compared to conventional shortest-path solutions and Pareto-optimal trade-offs can be computed efficiently using NSGA-II, enabling real-world applicability.

Future research should focus on evaluating the system's scalability in large, high-density networks, and on integrating additional criteria (e.g., pedestrian flow, temporary road closures, accessibility), leveraging the inherent flexibility of Pareto optimization in handling multi-objective problems. Furthermore, behavioral validation through controlled user studies would help quantify the actual impact of MODyPer-generated routes on mode-shift patterns.

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