UNIVERSITY OF TECHNOLOGY SYDNEY

OPTIMIZING URBAN MOBILITY: A MULTI-OBJECTIVE AI-POWERED PERSONALISED PEDESTRIAN ROUTE PLANNING SYSTEM

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Doctor of Philosophy

under the supervision of Dr. Fahimeh Ramezani and Dr. Mohsen Naderpour.

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Maryam Adel Saharkhiz declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computer Science/ Faculty of Engineering and IT at the University of Technology Sydney.
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Adele Saharkhiz
March, 2025

DEDICATION

To my beloved spouse, Hossein, whose unwavering love, encouragement, and sacrifice have been the guiding light of my journey. Your endless support has inspired me to reach new heights and overcome every obstacle along the way. This thesis is dedicated to you, with deepest gratitude and affection.

To my dear supervisor, Fahimeh, whose continuous support, guidance, and mentorship have been invaluable throughout my journey. Fahimeh, you were more than just a supervisor to me; you were like family. Your unwavering belief in my potential, your encouragement during challenging times, and your dedication to my academic and personal growth have made a profound impact on me. This thesis is dedicated to you, with deepest appreciation and admiration.

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Abstract

This thesis presents a comprehensive exploration into pedestrian navigation systems, addressing critical shortcomings and redefining the landscape of pedestrian route planning. Grounded in a systematic analysis of existing literature and research gaps, the study establishes clear and focused objectives to develop an innovative and adaptive route optimization solution.

The research introduces a Personalised Multi-Objective Pedestrian Route Planning System, designed to generate safe, accessible, attractive, comfortable, and overall pedestrian-friendly route by balancing multiple conflicting objectives such as safety, attractiveness, comfort, and accessibility. To ensure practical applicability, a post-optimization process is applied to select the most suitable solution from the generated Pareto front, aligning with pedestrian preferences.

Key contributions include the development of comprehensive hierarchical taxonomies for categorizing route choice factors by pedestrians, a novel multi-objective pedestrian route planning problem along with associated model and framework, and an advanced GIS-based methodology for pedestrian network data preparation. The study also integrates metaheuristic algorithms, particularly Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO) algorithm, to enhance decision-making in route selection.

The effectiveness of PB-MOACO is validated through a comparative evaluation against two benchmark algorithms: Multi-Objective ACO via Weighted Aggregation (MOACO-WA) expanded and customised for this study and Dijkstra's algorithm. Results demonstrate that PB-MOACO outperforms both benchmarks in generating safer, comfier and more pedestrian-friendly routes while maintaining reasonable computing times. Real-world validation using truth data (actual path lengths, safety conditions, comfort attributes, scenic status along the route) further confirms the superiority of the proposed approach over traditional methods.

Beyond academic contributions, this research has practical implications for urban mobility planning, pedestrian safety, and intelligent transportation systems. By addressing the limitations of existing pedestrian navigation systems and introducing an adaptive, user-centric approach, this study enhances personalized pedestrian routing, offering a more efficient, flexible, and safer navigation experience.

CHAPTER 1

INTRODUCTION

1.1 Research Background and Motivation

In the past few years, navigation systems have quickly converted to essentials part of the everyday life. Pedestrian navigation, in the meantime, has converted to an important practical and theoretical research subject in numerous location-based disciplines such as geographical information science, cartography outdoor and indoor positioning, psychology, neuroscience and spatial behaviour in sociology, (Fang et al., 2015). Pedestrian navigation emphases on how to effectively and efficiently design the guidance of the route from origin to the destination (Wang, 2018). Similar to the car navigation, pedestrian navigation systems (PNS) usually consist of three modules of route positioning, route planning and route communication / presentation (Huang & Gartner, 2009). Positioning aims to recognize the pedestrians' location using GPS. Route planning involves calculation of the pedestrian's desired route from origin to destination. The route communication module for pedestrians physically presents and visualize semantic route instructions enriched with landmarks (Gartner et al., 2011; Sevtsuk & Kalvo, 2021) in various forms such as audio, visual, 3D, hybrid, haptic, and augmented reality (Figure 1).

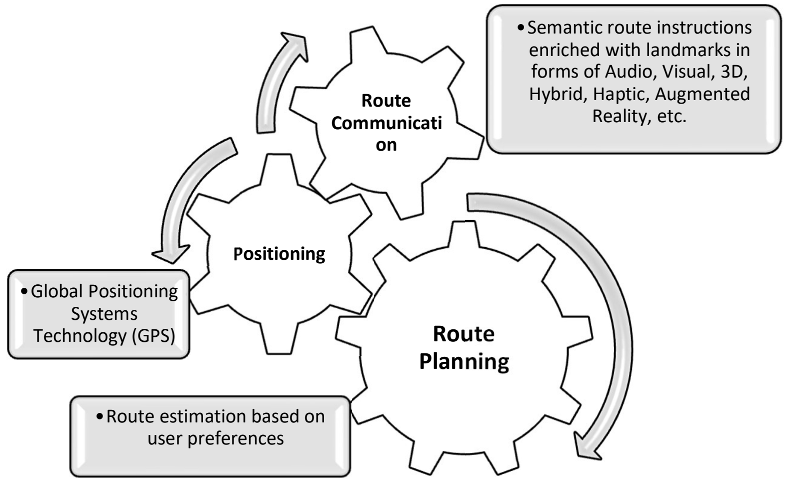


Figure 1.1 Main modules and critical components of pedestrian navigation systems (Huang & Gartner, 2009) (Diagram designed by the author)

Route planning as the significant module of any navigation system has an important role in real-world applications such as transport systems, communication networks, space applications, autonomous robotics, military guidance, and energy (Dib et al., 2017). Hence, it is also a broadly considered topic at intelligent transportation in pedestrian navigation services (PNS).

A vast literature review of the pedestrian route planning studies has revealed that four components of parameters, algorithms, decision making strategies and parallel implementation techniques are key elements for developing any optimum pedestrian route-planning framework (Fang et al., 2011; Talbi, 2009; Yao et al., 2018) (Figure 2).

Parameters refer to pedestrians' route choice determinant factors (Seneviratne & Morrall, 1985), whereas, Algorithms knowns as a computational engine for route estimation. They are a set of step-by-step mathematical operations employ to calculate the best path from origin to destination (Zadeh et al., 2016). Decision-making strategies employ for best route selection among a set of solutions based on user preferences (Vukmirović, 2010) and finally, parallel implementation techniques help to accelerate search engine and improve overall model efficiency (Talbi, 2009).

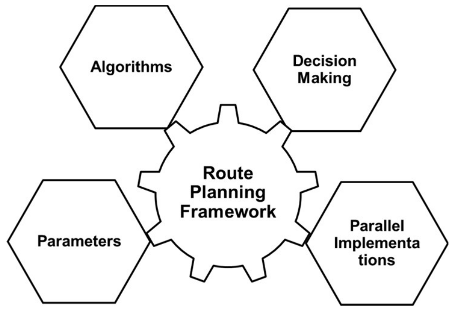


Figure 1.2: Illustration of route planning essential components (designed by the author)

This research aims to design and develop a complete optimization-based route planning system for pedestrians' heterogeneous groups based on their preferences in different scenarios. The specific objectives of this study involve delineating a comprehensive understanding of the parameters influencing pedestrians' route choices, employing advanced algorithms for precise route estimation, incorporating GIS techniques for network preparation, and developing cost function, and implementing decision-making strategies to enhance user-specific route selection.

The significance of this study lies in its potential to address critical challenges in pedestrian navigation systems. By focusing on the preferences of heterogeneous groups, the proposed route planning system aims to fill existing gaps in the field, offering a tailored and efficient solution for diverse user needs. The outcomes of this research hold promise for various practical applications, including improving navigation experiences for specific user demographics and enhancing overall efficiency in diverse real-world scenarios.

This research employs a methodology that intricately combines Geospatial data analysis, algorithm development, and user behaviour studies to achieve the outlined objectives. By adopting an optimization-based approach, the study seeks to contribute novel insights to the field of pedestrian navigation, offering a sophisticated solution that accounts for user preferences in different spatial contexts.

In the subsequent chapters, we will delve into the specific problem statement, research questions and objectives, research methodology, and a detailed outline of the thesis structure, providing a comprehensive understanding of our approach and findings.

1.2 Problem Statement

In recent years, the surge in popularity of pedestrian navigation systems, including widely used commercial products such as Google Maps, OpenStreetMap, Baidu Maps, and AutoNavi Map, has revealed significant shortcomings in their ability to cater to the diverse needs of pedestrians. Current systems, including these major platforms, exhibit several critical limitations:

I. **Single-Metric Optimization:** Current pedestrian route planning systems predominantly focus on optimizing a single metric, such as distance or time, neglecting the consideration of other critical criteria that play pivotal roles in users' decision-making processes (Yao et al., 2018).

II. **Limited Route Diversity:** The prevalent approach of employing shortest-path algorithms results in a lack of route diversity. Pedestrians are typically provided navigational assistance along the shortest or fastest route, overlooking potentially more suitable paths based on user references and environmental factors (Fang et al., 2017; Hashemi & Karimi, 2017).

III. **Street Path Centricity:** Pedestrian navigation systems commonly prioritize providing assistance on street paths rather than considering the close proximity to pedestrian pathways. This limitation fails to account for the nuances of pedestrian-friendly routes (Hashemi & Karimi, 2017)

IV. **Neglect of Pedestrian Preferences:** Unlike car navigation systems that incorporate user preferences, existing pedestrian route planning systems often fall short in catering to the diverse preferences and real needs of pedestrians in various situations (Haqqani et al., 2017; Novack et al., 2018).

V. **Weighted Objective Approach:** In scenarios where multiple criteria are considered, existing systems often resort to converting all objectives into a single metric using weighting approaches. This oversimplified approach neglects the real essence of multi-objective optimization, where all fitness functions should be optimized concurrently. The consequence is a loss of potentially valuable solutions and an exponential increase in runtime (Fang et al., 2017; Talbi, 2009).

Addressing these limitations is crucial for the development of a robust and user-centric optimization-based route planning system that considers diverse preferences, multi-objective optimization, and real-world pedestrian needs across various scenarios. This research endeavors to overcome these challenges and contribute to the advancement of pedestrian navigation systems that truly align with the dynamic nature of pedestrian mobility.

Research Motivation: Rationale Behind Developing This System for Pedestrians

Developing this system facilitates the creation of routes that consider pedestrian safety, traverse attractive urban areas, ensure comfort through manageable slopes, and maintain accessibility by minimizing distances. This iterative optimization process leads to the identification of the most efficient and pleasant pedestrian paths in urban environments.

1.3 Research Questions

The elucidation of precise research questions is paramount to the structured investigation and subsequent achievement of the defined research objectives. In this section, we articulate a set of focused inquiries that systematically guide the exploration of our research domains. Each research question aligns with a specific research objective, forming a cohesive framework for our inquiry into the development of a novel, multi-objective pedestrian route planning system. Through the following inquiries, we aim to delve into the intricacies of formulating the optimization problem, identifying key influencing parameters, designing innovative algorithms, implementing robust GIS methodologies, and evaluating the performance and validity of our proposed system. These research questions serve as beacons, directing our efforts towards a comprehensive understanding and solution to the challenges posed by existing pedestrian navigation systems.

Research Question 1: How can a novel multi-objective optimization route planning problem for pedestrians be theoretically defined, considering route choice parameters, path planning algorithms, and the limitations of existing pedestrian route planning systems?

Research Question 2: What are the critical route choice parameters that significantly influence pedestrian navigation, and how can they be effectively incorporated into a multi-objective optimization framework?

Research Question 3: How can a novel multi-objective pedestrian route planning algorithm/system be designed to address the identified parameters and preferences, providing an innovative and efficient solution for personalized navigation?

Research Question 4: What innovative methodologies can be employed in Geographic Information System (GIS) data collection, processing, and cost function calculation to ensure the accurate preparation of network data for pedestrian route planning?

Research Question 5: How can an experimental setup be designed to effectively implement the optimisation search algorithms, ensuring a comprehensive evaluation of their performance in the context of pedestrian route planning?

Research Question 6: How does the proposed multi-objective pedestrian route planning system perform in diverse scenarios within selected study areas, and what insights can be drawn from its evaluation in real-world applications?

1.4 Research Objectives

In pursuit of addressing the shortcomings identified in current pedestrian navigation systems and questions stated in the last section, this section outlines a set of clear and focused objectives that guide the research towards the development of an innovative and adaptive route planning solution. Each objective is strategically crafted to contribute to the overarching goal of creating a personalized, efficient, and multi-objective pedestrian navigation system. From conceptualisation and formulating a novel optimization problem to evaluating and categorising the authentic contributing parameters and designing and implementing cutting-edge algorithms, these objectives collectively drive the research towards a comprehensive framework poised to redefine the landscape of pedestrian route planning. This section delineates the roadmap for achieving these objectives, emphasizing the research's commitment to advancing the field of pedestrian navigation through thoughtful and systematic exploration.

Research Objective 1: Conceptualize a Novel Multi-Objectives Optimization Route Planning Problem for Pedestrians.

This objective aims to establish a robust conceptual foundation by defining a novel multi-objective optimization route planning problem for pedestrians. It involves a comprehensive theoretical delineation informed by a gap analysis in the existing literature, exploring route choice parameters, mathematical algorithms for path planning, and highlighting limitations in current pedestrian route planning systems.

Research Objective 2: Develop Innovative Hierarchical Taxonomies on Influential Route Choice Quality Parameters for Pedestrians

This objective focuses on pioneering the development of novel hierarchical taxonomies to categorize and analyse influential quality parameters shaping pedestrian route choices. Through a comprehensive investigation, authentic aspects aligned with pedestrians' real needs and preferences will be identified and structured hierarchically, presenting a groundbreaking contribution to the understanding of factors influencing personalized route planning.

Research Objective 3: Formulate a Novel Multi-Objective Pedestrian Route Planning Model.

This objective encompasses the formulation of the problem and the development of an innovative multi-objective pedestrian route planning model. The model caters to personalized route planning, addressing identified parameters and preferences, and represents a cutting-edge contribution to the field.

Research Objective 4: Develop an Advanced GIS Methodology for Multi-Dimentional Network Data Model.

This objective focuses on creating an innovative GIS methodology for graph network data modelling. It involves spatial data collection, and GIS network processing include quantification of Quality Parameters. This comprehensive methodology ensures accurate and efficient pedestrian network model through optimal network data preparation.

Research Objective 5: Design Metaheuristic Algorithm and Decision-Making Integration.

This objective focuses on designing and implementing the Ant Colony Optimisation (ACO) metaheuristic algorithm. It includes the development of a robust experimental setup and a systematic approach to find optimal solutions based on four different parameters. The integration of user preferences into the decision-making process ensures alignment with individual requirements, enhancing the practical applicability of the proposed route planning system.

Research Objective 6: Deploy Designed Algorithm in Real-World Scenarios and Evaluate Algorithm Performance.

The final objective involves testing the proposed multi-objective personalized pedestrian route planning solution through algorithmic deployment in selected study areas City of Sydney. The goal is to gain insights into the system's effectiveness and applicability in real-world scenarios, including diverse situations.

Research Objective 7: Conduct Comprehensive Performance Assessment and Algorithm Comparison.

In addition to Multi Objectives Ant Colony Optimisation via Weighted Aggregation (MOACO-WA), another search algorithms namely Dijkstra suitable for designing the shortest path for smart mobility are incorporated for a rigorous and fair comparison of solutions generated by our selected optimisation approach (Pareto-Based Multi Objectives Ant Colony Optimisation (PB-MOACO)). This comprehensive approach facilitates a thorough comparative analysis, ensuring a holistic evaluation of PB-MOACO efficacy and providing valuable insights into its performance compared to alternative algorithms.

In summary, these objectives collectively aim to contribute to the development of an advanced, user-centric, and efficient pedestrian route planning system that addresses the limitations of current approaches.

1.5 Research Significance

This research holds profound significance in reshaping the landscape of pedestrian navigation, transcending traditional paradigms and introducing innovative solutions to address critical limitations in current systems. At its core, the significance of this study is underscored by its potential to revolutionize the way pedestrians navigate their surroundings.

By prioritizing user preferences and authentic needs, the proposed multi-objective optimization-based pedestrian route planning system aims to redefine the user experience.

Current commercial navigation products often fall short in understanding and accommodating the diverse factors influencing pedestrian route choices. This research seeks to bridge this gap by introducing a holistic approach that considers a multitude of criteria simultaneously, promising a more nuanced and personalized navigation experience.

An integral aspect of this research lies in the development of a novel GIS methodology for network data preparation. This methodology not only ensures the accuracy and reliability of the route planning process but also represents a noteworthy advancement in geographical information science. It sets a precedent for sophisticated data processing techniques that extend beyond the scope of pedestrian navigation, influencing broader applications within GIS.

The introduction of cutting-edge multi-objective pedestrian route planning algorithms and frameworks, including the application of evolutionary-based ACO optimization approaches, marks a significant contribution to the field. These algorithmic advancements have the potential to redefine optimization techniques, not only within the realm of pedestrian navigation but also across diverse domains that leverage optimization for decision-making.

A distinctive feature of this research is its emphasis on user-driven decision-making. By incorporating a systematic ranking mechanism for parametrs based on user preferences, the study addresses a crucial gap in current pedestrian route planning systems. This approach ensures that the final recommended route aligns closely with individual user priorities, enhancing the overall usability and user satisfaction with the system.

The impact of this research transcends academic discourse, reaching into practical, real-world applications. Sectors such as transportation, communication networks, autonomous robotics, and military guidance stand to benefit from the improved efficiency and adaptability offered by an advanced pedestrian navigation system. The outcomes of this study, therefore, hold the promise of not only advancing scholarly understanding but also positively influencing the daily navigation experiences of individuals across diverse scenarios.

1.6 Research Methodology

In this study we present a methodology for the conception, creation, experimentation, and ultimate implementation of metaheuristic algorithms designed to address pedestrian route planning real-world challenges. This methodology, as articulated by Osaba et al. (2021), (Section 1.6.1), encompasses various critical facets that a metaheuristic solver must effectively navigate to enhance its reproducibility and facilitate its practical application.

1.6.1 A Tutorial On the design, experimentation, and application of metaheuristic algorithms to real-World optimization problems

Our approach adheres to a structured workflow illustrated in Figure 3 and Figure 4, representing the phase I and phase II of reference framework for employing metaheuristic algorithms in solving route planning optimization problem for pedestrians.

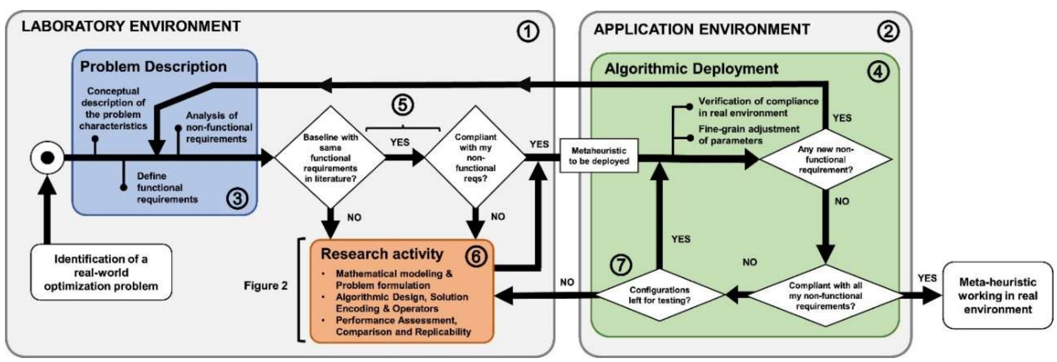


Figure 1.3 Phase I & Phase II - Visual representation of reference framework for employing metaheuristic algorithms in solving optimization problems (Osaba et al., 2021).

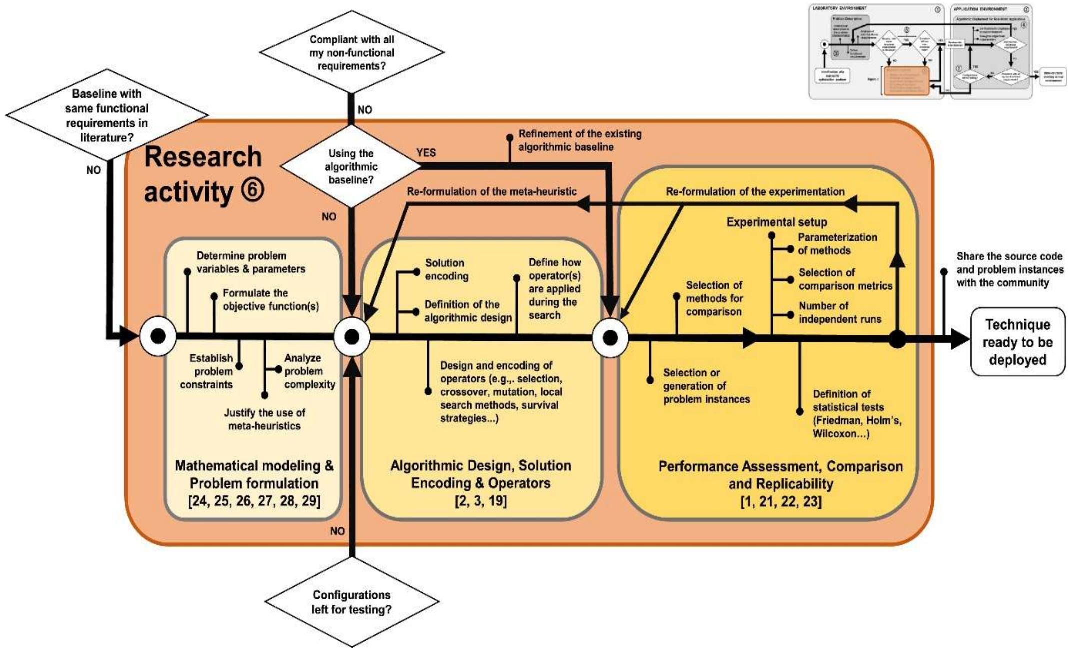


Figure 1.4 Phase II - Visual representation of the reference workflow (Osaba et al., 2021).

We delve into the entire spectrum, starting from the initial phase of problem conceptualization to the validation and practical utilization of the developed algorithm. As depicted in Figure 1.3 and Figure 1.4, the primary focus of this methodology includes the following key components:

I. Problem Definition

Initiating with the identification of a tangible problem requiring resolution, the research commences with the conceptual definition of the problem and the analysis of both functional and non-functional requirements. Stakeholder involvement, including researchers and developers, is strongly recommended during this high-level conceptualization phase.

II. Problem Modelling and Mathematical Formulation

This phase is dedicated to the thorough modelling and mathematical formulation of the optimization problem, building upon the conceptual groundwork laid in the preceding stage (Figure 1.5). This step is particularly crucial when dealing with novel problems not addressed in existing literature or lacking an adapted baseline or library.

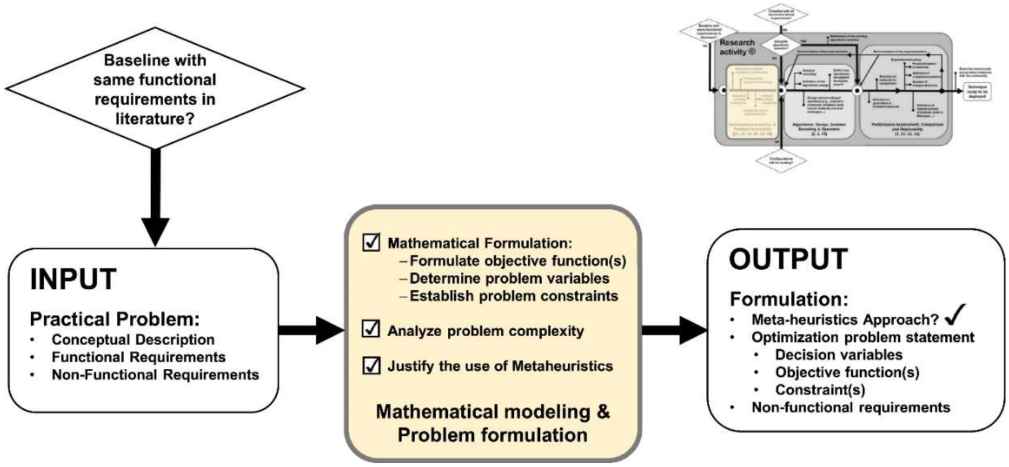


Figure 1.5 Workflow for Mathematical Modelling and Problem Formulation (Osaba et al., 2021)

III. Algorithmic Design, Solution Encoding, and Search Operators

The third stage involves the design and implementation of the metaheuristic algorithm or method. It is worth noting that parallel research may focus on refining an existing baseline or library within the scientific community (Figure 1.6).

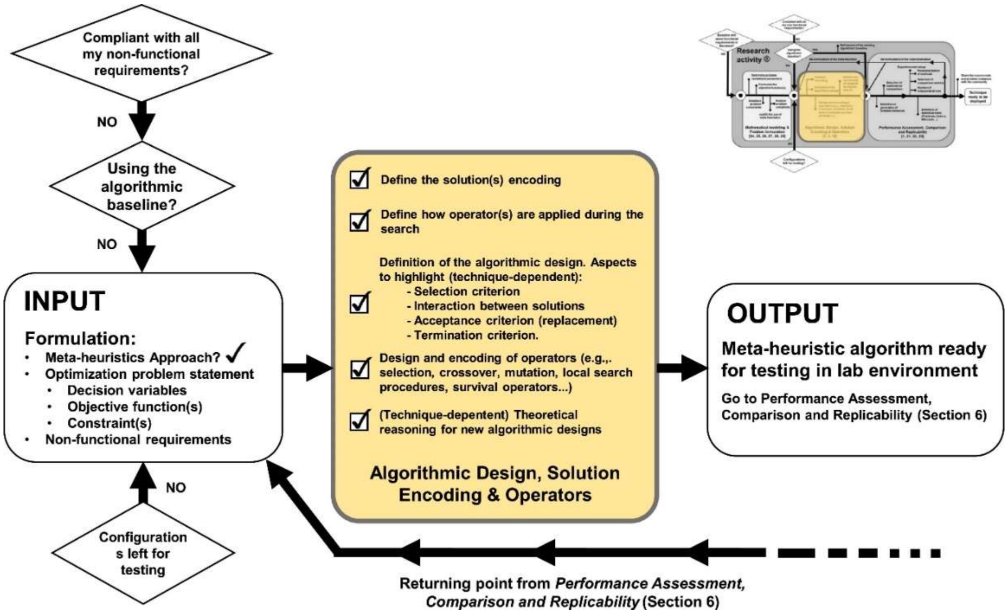


Figure 1.6 Algorithmic Design, Solution Encoding, and Search Operators (Osaba et al., 2021).

IV. Performance Evaluation, Comparison, and Replicability

This pivotal step is dedicated to the accurate assessment of the developed algorithms, ensuring their replicability and research consistency. Post the development or refinement of the algorithmic approach, a thorough performance analysis is conducted, significantly influencing the replicability and consistency of the research (Figure 1.7).

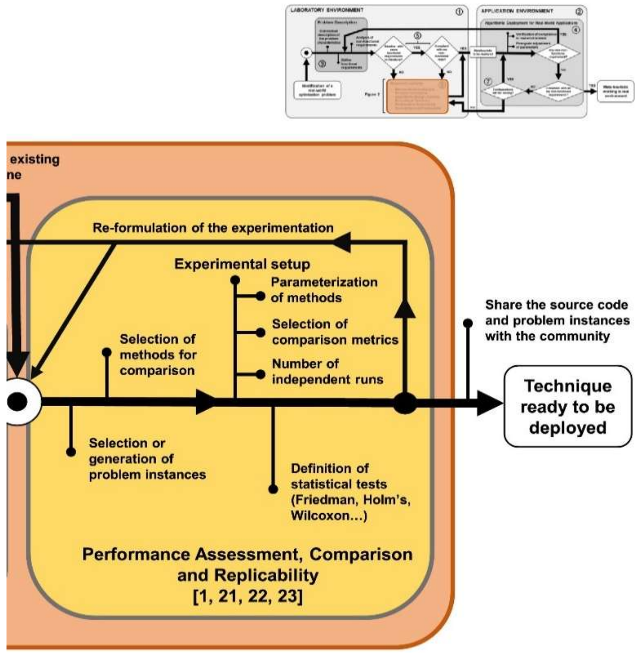


Figure 1.7 Workflow of Performance Assessment, Comparison and Replicability(Osaba et al., 2021).

V. Algorithmic Deployment for Real-World Applications

In the final phase, following the successful development and testing of the metaheuristic, the algorithm is deployed in a real-world environment (Figure 1.8).

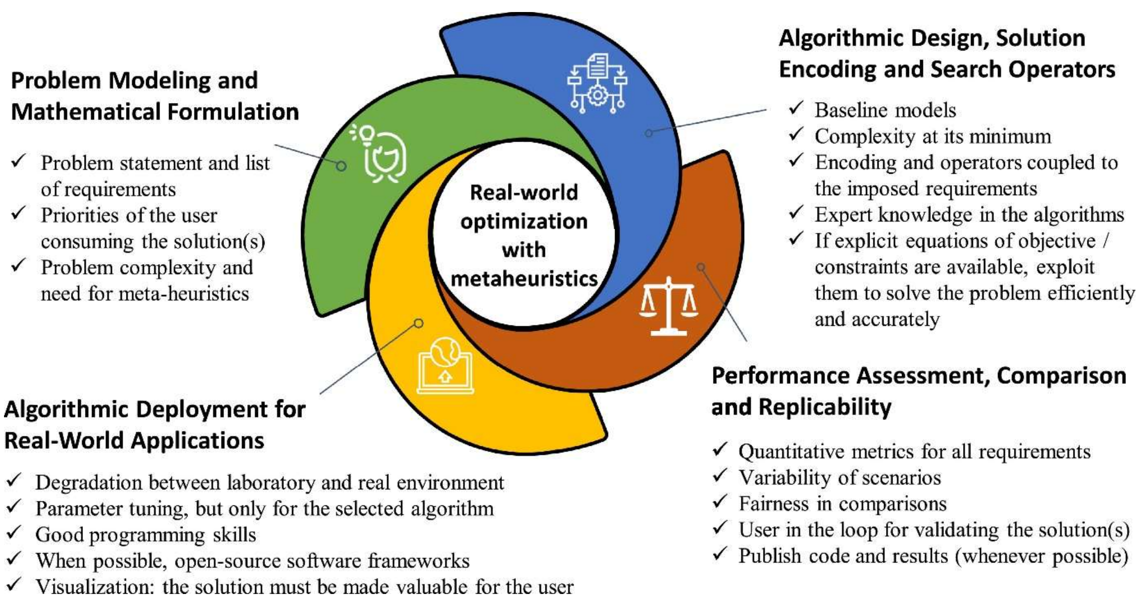


Figure 1.8 Real-world Optimization with Metaheuristics (Osaba et al., 2021).

This comprehensive research methodology ensures a systematic and thorough exploration of metaheuristic algorithm application, contributing to advancements in solving real-world optimization problems.

1.6.2 Thesis Research Methodology

Given the established research methodology framework, the study's research plan encompassed the subsequent steps, and outlined, and depicted bellow:

The methodology employed in this research is a carefully structured and systematic approach designed to achieve the outlined objectives. It encompasses a series of interconnected steps, each contributing to the development, evaluation, and validation of the proposed multi-objective personalized pedestrian route planning system.

Step 1. Select a Topic:

The research methodology commences with a comprehensive examination of the existing limitations in current pedestrian route planning systems. This involves a meticulous review of commercial products, such as Google Maps, OpenStreetMap, Baidu Maps, and AutoNavi Map, identifying their shortcomings and framing the research problem within the context of these deficiencies.

Step 2. Literature Review:

A thorough exploration of existing literature follows, delving into studies related to pedestrian route planning, multi-objective optimization, GIS methodologies, and algorithmic frameworks. This literature review serves as a foundation for identifying gaps, benchmarking against existing solutions, and integrating relevant theoretical frameworks into the research design.

Step 3. Finalise and Conceptualise the Multi-Objectives Optimization Research Problem:

The development of a novel multi-objectives optimization route planning problem for pedestrians is a pivotal aspect of the research methodology. This involves translating the identified user preferences and real-world needs into mathematical formulations, laying the groundwork for the subsequent algorithmic development.

Step 4. Determine and Categorise Route Choices Quality Parameters:

In parallel, efforts are directed towards the identification of parameters influencing pedestrian route choices. Real-world scenarios and user preferences are thoroughly analysed to ensure a comprehensive understanding of the contributing factors. This phase involves development of hierarchical taxonomies on influential route choice quality parameters for pedestrians.

Step 5. Mathematical Modelling and Formulation of Proposed Route Planning Problem:

Building on the identified multi-objectives optimization problem and parameter set, the research methodology includes the design of a novel multi-objective pedestrian route planning model and formulation of objective functions.

Step 6. Develop GIS Methodology for Network Preparation:

Simultaneously, a robust GIS methodology for network data preparation is developed. This includes the collection and processing of geospatial data, as well as the modelling of GIS networks. The integration of this methodology ensures the foundational data quality essential for accurate route planning.

Step 7. Computational Metaheuristic Algorithmic Design:

This step involves developing an experimental setup for Metaheuristic Algorithmic Design, Solution Encoding and Search Operators. This part ensures advanced algorithmic developments in pedestrian path planning.

Step 8. User-Driven Decision-Making Integration:

A key component involves the integration of the systematic ranking mechanism for parameters. This phase ensures that the proposed system aligns closely with user preferences, introducing a user-centric decision-making process into the route planning algorithm.

Step 9. Algorithmic Deployment for Real-World Scenarios and Performance Evaluation:

The methodology concludes with a comprehensive implementation and evaluation of the proposed multi-objective personalized pedestrian route planning system in the selected study area in Greater Sydney. This involves testing the system in various real-world scenarios, assessing its validity, and measuring its performance against predefined criteria and algorithms. Here is the summary of the implementation steps in real-world scenario:

- **Study Area Selection:** We start with selection of study area which has well-distributed pedestrian network throughout the area and harmonious blend of built-up areas, verdant green spaces, and notable landscape attractions.

- **Data Collection:** We start with the collection of different types of spatial data with sufficient accuracy from open sources data hubs.

- **Geospatial Contributing Parameters Generation:** The very first stage of our implementation part is to generate contributing parameters using geospatial information systems. Most of the significant parameters for users to make a decision based on will be creating in map concept with pixel formatting. These layers come in six classes of length distance (closest distance and shortest distance), tourist attraction landscape distribution map (aesthetic and scenic), the safety of the route, the safety of the environment, and gradient map (maximum slope and vertical distance).

- **Multi-Dimensional Network Modelling:** In this part, we will model our path networking. The values for entire contributing factors will be assigned to each stretch of pedestrian network. Then, the pedestrian network will be updated by calculated values of the length, crime Safety, Environmental Safety, Difficulty and Attraction of each segment to the generation function.

- **Path Planning Computation via Multi-Objective Optimization Algorithm**: In this section, three different models will be applied on the updated pedestrian network namely, Normal Ant Colony, Modified Ant Colony Optimization Approach and Dijkstra's algorithm.

- **Decision Making:** In this study, while employing the Ant Colony Optimization (ACO) algorithm for personalized multi-objective pedestrian route planning, the focus remains on obtaining a single optimal or near-optimal solution. However, to enhance the decision-making process and cater to user preferences effectively, a novel approach involving user-weighted criteria is adopted. By incorporating user-defined weights for each criterion, derived from individual preferences and priorities, the decision-making process is personalized and tailored to the specific needs of the user. These weights influence the ACO algorithm's exploration of the solution space, directing it towards solutions that align closely with user preferences. This integration of user-weighted preferences adds a layer of customization and adaptability to the route planning process, ensuring that the **generated solution** not only meets the optimization objectives but also reflects the unique preferences of the user. Such an approach contributes to the development of more user-centric and personalized route planning systems, which are essential in enhancing user satisfaction and overall usability in various real-world applications.

- **Accuracy assessment:** The results of all implemented models then will be assessed based on time efficiency, capability to work on large scale, and performance optimality.

Step 10. Comparative Analysis for Performance Evaluation:

In this phase, we introduce a spectrum of alternative, often less intricate search algorithms tailored for smart travelling. Our primary emphasis lies in providing a concise examination of the strengths and weaknesses of these algorithms. Additionally, we delineate the standard conditions governing their deployment and define the scenarios employed for rigorously assessing the PB-MOACO algorithm. This stage is pivotal in establishing a comprehensive benchmark and facilitating an insightful comparison of algorithmic performance.

Step 11. Documentation and Reporting:

Documenting the research process, methodologies, and results for comprehensive reporting in academic publications and presentations.

In summary, the research methodology is a holistic and iterative process that combines theoretical foundations, algorithmic innovation, GIS methodologies, and user-centric decision-making to address the identified limitations in pedestrian route planning systems. This strategic approach is designed to ensure the development of a robust, adaptable, and user-friendly system that meets the diverse needs of pedestrians in different scenarios.

In the following flowchart the research methodology and the relation between research objectives are illustrated (Figure 1.9).

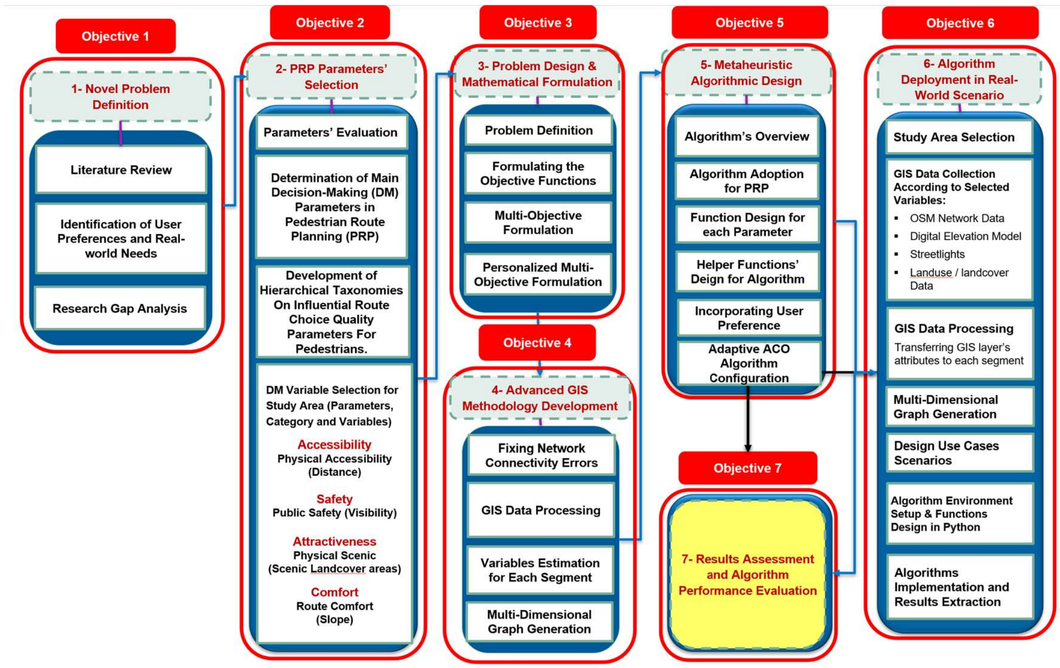


Figure 1.9: Research methodology framework covering relevant objectives.

1.7 Publications

Table 1.1 List of research publications

Objectives	Status
Saharkhiz, M.A., Pradhan, B., Rizeei, H.M. and Shariff, A.R.B.M., 2018, January. Extraction of forest plantation extents using majority voting classification fusion algorithm. In *Proceedings-39th Asian Conference on Remote Sensing: Remote Sensing Enabling Prosperity, ACRS 2018*.	Published
Saharkhiz, M.A., Pradhan, B., Rizeei, H.M. and Jung, H.S., 2020. Land Use Feature Extraction and Sprawl Development Prediction from Quickbird Satellite Imagery Using Dempster-Shafer and Land Transformation Model. *대한원격탐사학회지*, *36*(1), pp.15-27.	Published
Pedestrians Route Planning Systems: Hierarchical Taxonomies on Influential Route Choice Quality Parameters (A Selected Review)	Paper Submitted

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The Pedestrian Route Planning (PRP) domain has witnessed significant advancements in recent years, driven by the increasing demand for optimized wayfinding solutions. This chapter thoroughly examines the current state-of-the-art in PRP, focusing on various aspects such as routing algorithms, human navigation/wayfinding, computer-based route planning, user-centric context awareness concepts, and route choice criteria.

The subsequent sections provide a structured exploration of key components within the PRP domain, each contributing to a comprehensive understanding of the field. Beginning with an analysis of Pedestrian Navigation Systems (PNS) in section 2.2, the review progresses to discuss human navigation/wayfinding (section 2.3) and computer-based route planning (section 2.4).

Furthermore, the review delves into the significance of user-centric context awareness concepts in pedestrian navigation (section 2.4.1) and explores route choice criteria in pedestrian route planning systems (section 2.5). Section 2.6 examines personalized multi-criteria pedestrian route planning (PMPRP), highlighting the importance of catering to individual pedestrian preferences.

The review then focuses on optimization algorithms for pedestrian route planning in section 2.7, including both single-objective and multi-objective optimization approaches. Sections 2.7.1 and 2.7.2 provide an overview of single-objective and multi-objective optimization problems/algorithms, respectively.

In section 2.7.2.1, the review discusses single solution-based metaheuristics algorithms, while section 2.7.3 explores exact or mathematical program-based algorithms and metaheuristics algorithms. Section 2.7.4 further categorizes metaheuristics algorithms into population solution-based metaheuristics, including genetic algorithms, multi-objective swarm-intelligence-based approaches, artificial bee colony algorithms, ant colony optimization algorithms, and particle swarm optimization.

The chapter concludes with a research gap analysis and key contributions (section 2.8), highlighting unresolved issues in pedestrian route planning, such as pedestrian route choice quality parameters, computational algorithms, and path selection decision-making. Through this structured review, the chapter sets the stage for the development of a novel approach to pedestrian route planning, grounded in a thorough understanding of the current state-of-the-art and informed by identified research gaps.

2.2 Pedestrian Navigation Systems

Navigation systems are planned to ease users' navigation tasks in unacquainted environs (Gartner et al., 2011). Car navigation became enforceable earlier than pedestrian navigation because of its simpler and more restricted nature. Sticking to the street network of an area, car navigation systems these days propose developed services (Furukawa, 2015).

According to Furukawa (2015), the increased need for movement in the space, rather than along the street networks, motivates the designers to focus on the pedestrian. Pedestrian navigation, consequently, acts as the interface between users and their surroundings. From the early and primary versions of navigation systems to what we are using nowadays, pedestrians have been counted as users who move slowly without walking limitations and have a path network in their origin and destination directions. The dissimilarity between pedestrian and car navigation is mainly related to the following matters (Corona & Winter, 2001; Rehrl et al., 2007).

- **Cognition (Perception) of the space:** obeying traffic rules and focusing on the traffic streams makes the car drivers less aware of their surroundings, whereas this is not the situation for pedestrians who have an extra chance to observe their environments.

- **Greater freedom degree** for pedestrians means they are not restricted to only street networks. In other words, they are free to transfer everywhere on every route.
- **Resolution or details of space** are dissimilar for pedestrians and car drivers. Reduced speeds, as well as increased capacity of perception, let pedestrians distinguish additional details.
- **Less rapidity of motion** for pedestrians makes their sensing of the environment change. Conversely, GPS does not work correctly at prolonged speeds.

With the obtainability of GPS signals, a small form of features, less power consumption, and a very high degree of movability, navigation systems are converting to one of our common accessories these days. The word “ubiquitous navigation” is what new generations of navigation systems promise in which all navigational requirements are achieved closely in all circumstances.

Like other navigation systems, Pedestrian Navigation Systems consist of three key components (Figure 2.1): **Positioning**, **Route Planning** or **Calculation**, and **Route Communication** or **Guidance** (Huang & Gartner, 2009).

Positioning aims to identify the location of the pedestrian. Positioning in outdoor navigation often utilizes a global positioning system (GPS), which is not typically obtainable for indoor navigation (Wang, 2018). Positioning in covered navigation is usually done with the help of Radio-Frequency Identification (RFID), WiFi, Bluetooth, Ultra-Wideband (UWB), and dead reckoning. Route planning involves determining and planning the route from origin to destination. In the case of route communication, different interface techniques such as verbal instructions, mobile maps, augmented reality (AR), and 3D could all be beneficial (Taylor, 2013).

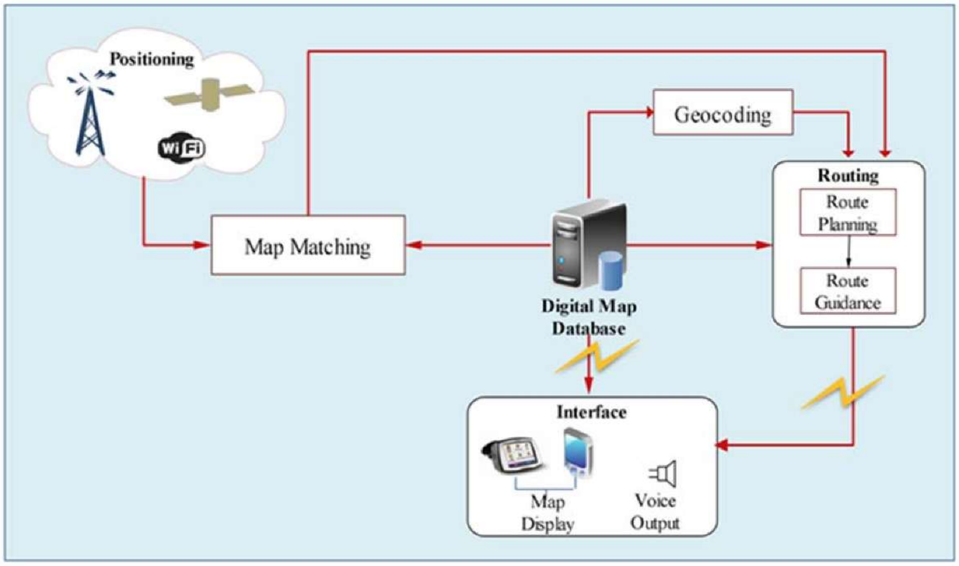


Figure 2.1: Main components of navigation systems

As mentioned earlier, this research mainly focuses on the route planning module, which focuses on computing the most appropriate route for pedestrians from an origin to a destination. It thereby assists users in solving the main problem in wayfinding:

"How to get to the destination based on user preferences".

The following sections introduce an overview of the basic concept of human wayfinding and computer-based route planning.

2.3 Human Navigation/Wayfinding

Montello (2005) describes navigation as "goal-directed and coordinated motion through the surroundings by organisms or intelligent machines". According to (Stea et al., 1977), navigation comprises four processes: orientation, route planning, staying on the correct track, and finding the destination. Equally, (Montello, 2005) conceptualized human navigation as composed of wayfinding as well as locomotion. Based on this definition, Wayfinding is an organization as well as the decision-making part of the navigation process, and it needs to be aware of where to go and how to reach there. Wayfinding requires a destination, a physical place we want to attain. This destination is frequently situated outside of our instant environments. Therefore, with the intention of making route choices, internal memories or external artefacts, such as maps, are regularly engaged throughout wayfinding.

In return, locomotion requires that we travel along a decided route effectively, plus coordinate body movements regarding surroundings. Throughout path following (locomotion), user constantly monitors their local environments. Objects of the real world (local surroundings) are assessed with memoirs kept internally or exterior artefacts such as maps for path validation (Gartner & Hiller, 2009). This procedure remains until the destination is touched.

In summary, good navigation involves knowing where to go and how to reach there (the wayfinding section of navigation); it also needs moving along a planned route in a planned direction without having coincidences or getting needlessly delayed (the locomotion section of navigation) (Montello & Sas, 2006).

2.4 Computer-based Route Planning

The computational part of the routes in route planning has received significant attention from researchers over the last decade. Computer-based route finding aims to calculate the "best" path from an origin to a destination (Gartner et al., 2011). Classic methods, namely the Dijkstra algorithm and A* algorithm, are typically used to automatically design a route over road networks (Zhan & Noon, 1998). Usually mentioned algorithms often provide the fastest routes and shortest distance routes. Lately, algorithms for discovering optimal routes considering more criteria have also been recommended in the literature (Andreev et al., 2015), which will be reviewed in section 2.8, "Optimisation Algorithms for Pedestrian Route Planning".

2.4.1 User-Centric Context-Awareness Concepts in Pedestrian Navigation

Pedestrian navigation (PN) is one of people's most fundamental spatial behaviours, skills, and services and is very helpful when encountering unfamiliar environments (Fang et al., 2015). Current research or industry usually views pedestrian navigation as process-oriented or goal-directed, location oriented or even data centric. Process-oriented and goal-directed systems do not pay much attention to people's preferences. The aim behind data-centric systems is to collect more non-spatial and spatial data because it was believed that this would increase the system's acceptability. A people-centric pedestrian navigation approach understands pedestrians' needs, limitations and constraints and integrates this understanding into the design process (Gartner et al., 2011). According to Fang's research (Fang et al., 2015), which is based on "Maslow's Theory", all innovative pedestrian navigation theory and technologies should focus on people-centric cognition, understanding, interaction, and preference so that they can service people in comfortable, respectful, and confident ways to meet pedestrian's needs in all aspects of physical sense, physiological safety, and mental satisfaction. Therefore, an ideal pedestrian navigation system should be researched and designed using a people-centric approach rather than process-oriented and goal-directed methods.

To meet user demands as a user-centric system, the navigation system must use path-finding algorithms in order to meet several objectives simultaneously (Masoumi et al., 2019). In real life, for instance, several costs may be associated with a single tour. Moreover, the objectives may not always be limited to cost. In fact, numerous other aspects, such as balancing workloads (time, distance and so on), can be taken into account simply by adding new(Goetz & Zipf, 2011). Thus, user-centric route planning is considered as a multi-objective problem.

2.5 Route Choice Criteria in Pedestrian Route Planning Systems

In the last decade, many routing services, such as Google Maps, have been created for pedestrians. The mentioned services are valuable in pushing users to utilize walking mode instead of their private cars, that cause decreasing the production of CO_2 emission, along with enhancing the traffic flow. The purpose of personalized pedestrian route planning is to offer an optimal route between origin and destination by considering the importance of effective criteria based on user preferences. This proposed route might be a combination of various walking track modes and a different number of criteria. The criteria for choosing a route are critical concerns related to pedestrian wayfinding approaches. Numerous researches in personalized pedestrian route planning using dissimilar criteria have been done in recent years. In the following sections, we present an overview of pedestrian route planning algorithms with a different number of criteria under categories of one criterion (single criterion), two criteria (Bi-Criteria) and more than two criteria, namely multi-criteria.

2.5.1 Single-Criteria Pedestrian Route Planning

In this section, we discuss some research that considered only one criterion. Yusof et al. (2015) employed distance as a key parameter to calculate the shortest possible path for visually impaired people to support them safely throughout their journey. In a similar attempt, but this time for people with disabilities, Neis and Zielstra (2014) worked on the generation of a friendly routing network based on collaboratively collected geodata provided by the OpenStreetMap (OSM) project. Their new representation of a routing graph could be used in several map applications and devoted to people with impaired mobility.

2.5.2 Bi-Criteria Pedestrian Route Planning

In the literature, more effort has been devoted to the optimization of pedestrian route planning by considering two criteria. Examples include using vertical distance and the maximum slope for the study by Rahaman et al. (2017a). The aim of their study was to design a journey planner that includes the accessibility of the route, as well as the standard metrics, such as distance and travel time. They defined two metrics to reveal the accessibility of a route concerning the maximum slope and total vertical distance.

Several studies on route planning for pedestrian navigation have considered safety-related issues along with typical route metrics like distance or travel time. Galbrun et al. (2016) defined the SAFEPATHS problem as a Bi-objective shortest-path problem that takes into account two criteria: public safety (crimes) and Distance. They utilize crime data to provide safe urban navigation by developing a risk model for an urban road network that is based on civic datasets of criminal activity as well as on city-dwellers' mobility traces.

Yao et al. (2017) consider two parameters of safety and distance as two critical criteria for finding optimized paths in smart cities. In their research, they considered the safety index in navigation services and conducted experiments on the safety index map constructed based on the historical urban data of New York City. In the final map, each criterion was quantified while users could see all the possibilities with risk and distance options.

2.5.3 Multi-Criteria Pedestrian Route Planning

Multi-criteria route planning computes a route from a point of origin to a road network's destination point, taking into account three or more criteria. Multi-criteria route planning offers pedestrians a diversity of criteria for route planning (BOZKURT KESER et al., 2016). The criteria could be the route with high scenic potential, the shortest travel distance, the safest path regarding crime or natural hazards, or a path with minimum vertical distance or slope. Safety in terms of road light coverage and traffic volume in route planning for pedestrian navigation at night has been studied by Fang et al. (2017).

2.6 Personalized Multi-Criteria Pedestrian Route Planning (PMPRP)

A personalized pedestrian route planner delivers a suitable route based on minimizing a grouping of user-defined criteria, such as travel time or distance, quantity of traffic lights, and types of routes. The selection of the proper criteria and determining the position of each are related to user preferences (e.g., some travellers prefer the least travel time, while others seek small aesthetic roads). A route that includes the user's preferences is eventually more ideal than the route with the shortest travel time or distance. In a system of route planning, user preferences for each key criterion can be recognized manually by the system developer (or by the user) or automatically by determining regularities and patterns in the repeated route choice behaviours of the users. Systems that employ the manual way are called "adaptable personalized route guidance systems", while systems that apply automatic methods are called "adaptive, personalized route guidance systems" (Zipf et al., 2006).

Table 2.1 shows a centralised summary of the state-of-the-art personalization route planning systems with different criteria using optimization algorithms but single solution-based approaches. All the studies solved the problem by converting multiple objectives to single objectives primarily via weighting sum approaches.

Table 2.1 list of conducted studies on Personalization route planning literature with consideration of different criteria.

References	Criteria	Key Features	Method	Cons
(Sahelgozin et al., 2015)	Length, Safety, Difficulty and Attraction	Context-awareness and User-awareness capabilities	AHP weights	Using weighting methods
(Huang et al., 2014)	comfort, safety, attractiveness, diversity, and relaxation	Collecting people's affective responses to environments for enhancing computer-based route planning	crowdsourcing	They collect only people's feelings toward the roads! Apply only on a small scale.

(Niaraki & Kim, 2009)	Segment length, current time and speed, and path-allow-vehicle type (paths allow for special vehicle type) are criteria for constant context information. Furthermore, variable context information is various criteria such as traffic, weather, safety, facilities, and tourism.	personalized user-centric route-finding application	Multi-attribute decision-making methods (AHP)	Converting multiple objectives to single objectives. Applied on only a small scale
(Pahlevani et al., 2019)	Time, Fare, Minimum changes of transportation modes	personalized route finding	Fuzzy AHP QOWA weighting method	Using weighting methods
(Gartner et al., 2011)	Simplicity, safety, attractiveness, and convenience.	human-centred pedestrian navigation systems	DIJKSTRA's algorithm	Using exact method

2.7 Optimisation Algorithms for Pedestrian Route Planning

Selecting a suitable algorithm is the next key challenge in developing personalized pedestrian route planning. Numerous optimization algorithms can address pedestrian route planning despite its classification as an NP-complete problem. However, a significant drawback is the absence of a comprehensive framework categorizing these algorithms for practical application in pedestrian route planning. To address this gap, we have developed a comprehensive framework that systematically categorizes optimization algorithms based on their suitability for solving pedestrian route planning challenges (Figure 2.2).

To better understand the advantages, gaps, and drawbacks of previous research, in subsequent subsections, we will discuss and critically analyse related works under elements of this category.

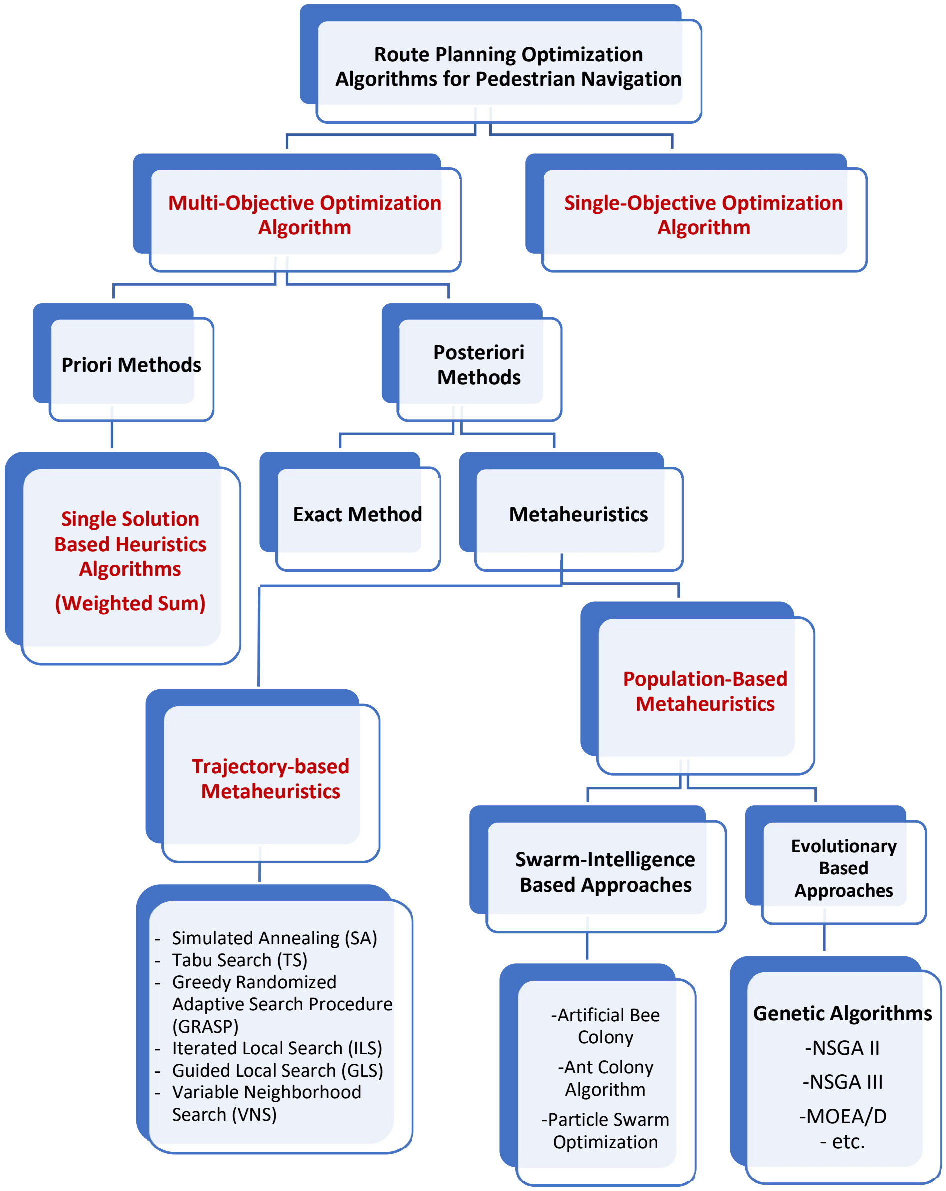


Figure 2.2 Classification of optimization algorithms for pedestrian route planning

2.7.1 Single-Objective Optimization Problem/Algorithm

In decision analysis models (Triantaphyllou, 2000) it is equal to single objective decision making (SODM) approaches. Their main purpose is to discover best solution with maximizing or minimizing of a single objective function value. Single-objective optimisation problem is straightforward problem where there exists only single objective function to optimise with only one optimal result to be gained. Depending on preferred objective, the problem is solved for the user. If only one objective function is chosen, then the problem is solved in a single objective style using a simple algorithm, otherwise multi-objective algorithms are used.

Route planning is an essential service in the navigation system. Yet, most of commercial spatial applications deliver an optimal path that only minimize one metric such as time or distance, or other costs, while disregarding other important criterion (Yao et al., 2018).

As an example in this domain, we can mention two common heuristic-based algorithm for shortest path calculation which are Dijkstra and A* algorithm (single solution shortest-path algorithm) (Ferguson et al., 2005). These two algorithms effectively give the optimal route for various research on route planning problem. For example, route planning method by means of Dijkstra's algorithm for indoor space to navigate blinded users (Wu et al., 2007) and also the fusion of Floyd algorithm and Dijkstra to expand path planning for mobile robot in life science laboratories (Liu et al., 2012). However, there are drawback to these algorithms as they are computationally expensive and becomes incompetent when the dimension of the problem stays large.

2.7.2 Multi-Objective Optimization Problem/Algorithm

In decision analysis models it's also called Multi Criteria Decision Making (MCDM). The multi-objective optimization route planning is widely applied for quality of services (QoS) routing in the communication network, motion design in the robotic control and navigation in the transportation system. It is well known that the route planning with multi-objective is an NP-complete problem (Garroppo et al., 2010). There are two main approaches to solve Multi-Objective Optimization Problem (MOOP) in route planning: **Priori method** and **Posterior method**

2.7.2.1 Priori Methods

~~Multi attribute decision making (MADM) is equivalent term of Priori methods in decision analysis models.~~

Priori methods convert a multi-objective problem into a single-objective problem. By using a weighted-sum function with a weight vector, all objectives are converted into a single objective. This process allows the use of any single-objective optimization algorithm, but the obtained solution depends on the weight vector used in the weighting process.

The priori method only obtains a particular compromise solution according to the weight vector. However, weights for various objectives are defined by user preference prior to search. In the other word, a priori Preference Articulation make decisions before searching (Arbel, 1989). The solution of the priori approach is often non-optimized, first because during the whole optimization process, the bias will be imposed. Second, it is problematic to define the weight vector prior to search due to diverse magnitudes between multiple objectives.

Another extra point is that even when decision-makers confidently assign clear weights to each objective, framing the problem as a multi-objective optimization can lead to higher-quality solutions. This approach offers two key advantages: (1) multi-objective search helps escape local optima by leveraging the Pareto non-dominated relationship between solutions, allowing for broader exploration of the solution space, and (2) variations in the scale of different objectives have minimal impact, ensuring a more balanced and effective optimization process (Chen & Li, 2023).

- **Single Solution Based Metaheuristics Algorithms**

Single solution-based metaheuristic algorithms can be considered as Priori methods. They have been used for path planning in the recent literature (Jonietz, 2016; Niaraki & Kim, 2009; Pahlevani et al., 2019; Sahelgozin et al., 2015). These studies have converted multi-objective route planning to a single-objective using strategies such as using a weighted sum of the criteria (Fang et al., 2011) and the problem is not solved in real mode of multi-objective in which all fitness functions are optimized concurrently.

2.7.2.2 Posteriori Methods

As in mono-objective optimization, the optimization algorithms that can be used to solve Multi-Objective Optimization Problems (MOPs) can be categorized into exact and Metaheuristics (approximate) algorithms (Talbi, 2009). Figure 2.3 shows overview of classical posteriori optimization methods.

Unlike Priori methods, in posteriori approaches, a Preference Articulation search take place after decision making. It first acquires a set of Pareto optimal solutions, then, the planner/decision maker chooses the most appropriate one from the Pareto optimal solution set according to the user's preferences. The user preference can be also well-defined as a weight vector for number of objectives. In the posterior method, the weight vector is defined after process of optimization. The planner is capable to know the range of each objective in keeping with Pareto optimal solutions. Thus, it is easy to design the weight of vector by normalizing all objects into the same order of magnitude (Yao et al., 2018).

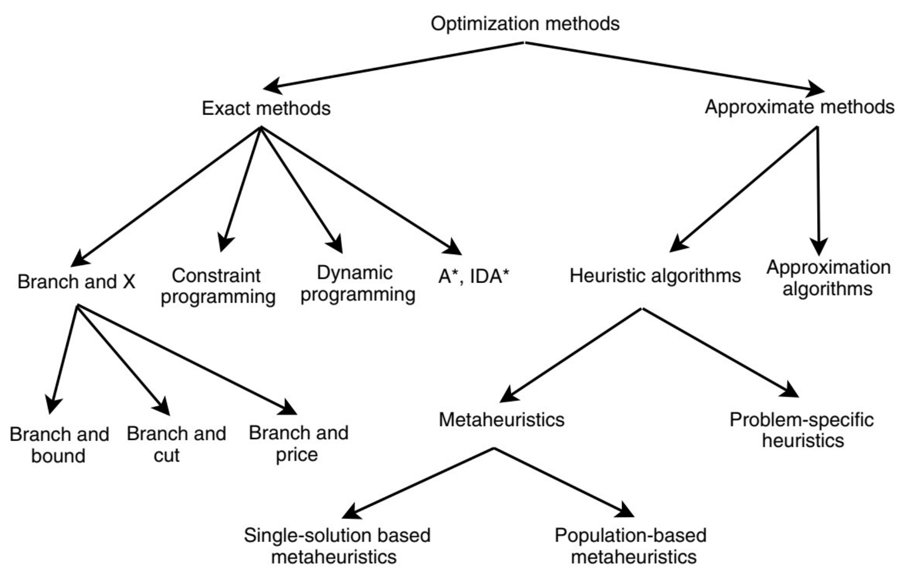


Figure 2.3 Classical Optimization Methods (Talbi, 2009)

2.7.3 Exact or Mathematical Program Based Algorithms

Numerous exact posterior methods are based on the Dijkstra's algorithm to acquire exact Pareto optimal results for route planning (Mallapur et al., 2016; Zhang et al., 2013). For the shortest path problem, Martins suggests a label setting algorithm (MLS) (Martins, 1984). As a matter of fact, MLS is a straight adjustment of the classic Dijsktra's algorithm in which dominance test is exchanged on the min operator. In 2006, Gandibleux, proposed an extension of Martins' label setting algorithm (EMLS) (Gandibleux et al., 2006). Since these labels can better the designation of optimal paths, EMLS algorithm adjusts the non-dominated test by concerning the weakly non-dominated labels.

In the literature, more attention has been devoted to bicriteria optimization problems by using exact methods such as branch and bound algorithms, branch and cut ,A* algorithm, and dynamic programming (Talbi, 2009). Despite the fact that these methods can obtain optimal solutions, but when they are performed to a large-scale network, the computational complexity of them getting tremendously high (Yao et al., 2018). In the other words, exact search methods are operative for small sizes problems. Furthermore, given the concurrent difficulties of NP-hardness complexity of problems and the multi-criteria on framework of the problems, for problems with more than two parameters, there won't be many efficient exact techniques. Nevertheless, there exists some new developments in this area, with some exact approaches recommended in the literature for biobjective (Lemesre et al., 2007) and multi-objective problems (Abounacer et al., 2014).

2.7.4 Metaheuristics Algorithms

Dijkstra and A* as traditional algorithms in route planning are difficult to adjust with multi-objective mode (Medhi & Ramasamy, 2017). Due to defects of exact methods in multi-objective problems, researchers have started to focus on metaheuristics algorithms which can be employ on a wide range of problems (Sörensen et al., 2018).

The recent advances achieved in Metaheuristic multi-objective optimization algorithms have supported their use in multi-objective route planning (Masoumi et al., 2019).

According to (Dib et al., 2017) the main motivation behind using metaheuristics in route planning instead of other methods stems from their ability:

- To deliver near optimum solutions in acceptable computational time.

- Offering flexibilities and high performance to cover a number of optimization categories (Mono criteria, multi-criteria) in dynamic, static or even stochastic modes.

- To produce a reasonable sub-optimal solution in a little time, specially in multi-objective optimization problems.

- To apply on large-scale or many criteria problems.

2.7.4.1 Population Solution Based Metaheuristics

The metaheuristic achieves an imitation procedure by implementing stochastic operatives among the population of possible solutions till getting convergence which can be described by using a given principle. The Population-based metaheuristic method that known as P-metaheuristic segment numerous shared solution theories which can be observed as a tangible iterative enhancement in any populace of solutions. Once the population was initiated a new set of solutions can be generated. And then, the new solution is combined with the previous one via selection processes. The search procedure will be stopped if any given precondition get satisfied which called stopping criterion. Several algorithms can be categorized into the metaheuristic approach including, artificial immune systems (AISs), estimation of distribution algorithms (EDAs), evolutionary algorithms (EAs), scatter search (SS), bee colony (BC), and particle swarm optimization (PSO) (Talbi, 2009).

In the subsequent sections, pedestrian route planning literature on multi-objective (MO) population-based metaheuristics includes (MO) Evolutionary Algorithms or (MOEAs) and (MO) Swarm-Intelligence Based are considered.

I. Multi-Objective Evolutionary Algorithms for Route Planning Optimisation

Theory:

Dissimilar with EA in a single objective method, where entire entities of the population combine to one single ideal result, multi-objective EA (MOEA) method ought to develop and attain all the population of optimum solutions. Therefore, in the final optimum result of the multi-objective procedure, every single solution can be considered as an optimum result regarding the entire objectives. Even though MOEA is basically according to EA theory, it yet needs some supplementary modules to effectively serve multi-objective issues.

This part explains three fundamental search mechanisms that are essential requirements in MOEA to monitor the population over the uniform diversity and precise convergence. These mechanisms are Elitism, diversity preservation, and fitness assignment.

a) **Elitism:** to avoid the valuable solutions getting damage through the incremental procedure. This is achievable by preserving an archive of desired results that were found out formerly during the evolutionary development.
b) **Diversity Preservation:** this search mechanism tries to sustain and expand the possible population of solutions. In fact, sharing scheme (Goldberg & Richardson, 1987) intensely relies on a priori information to identify a certain threshold value for gauging a differenced metric among several solutions. In contrary to sharing scheme, crowding scheme (De Jong, 1975) quantifies the thronging metric of a bunch of nearby solutions individually.
c) **Fitness Assignment:** translating the vector part of functions of assessed objective for a target solution in a particular qualitative significance that stimulates merging of the Pareto obverse. Pareto based scheme (Sbalzarini et al., 2000) uses the dominance theory to monitor the optimization development, while indicator based scheme (Zitzler & Künzli, 2004) relies on a quantified measurement for presentation.

Based on the mentioned search systems, multiple MOEA can be designed and applied by the mixture of appropriate structures. For example, the Nondominated sorting genetic algorithm II (NSGA-II) includes non-dominance organizing, elitism assortment procedure and crowding space transfer. Basically, the strength Pareto evolutionary algorithm-2 (SPEA-2) employs no dominance and fine-grained suitability transfer with nearest neighbour (NN) density approximation as well as archive truncation technique (E Zitzler et al., 2000). While the archive based micro-genetic algorithm-2 (AMGA-2) mixes adapted crowding space transfer, no dominance sorting, and exterior archiving (Tiwari et al., 2011). MOEA optimization techniques like AMGA2, NSGA-II, and SPEA2 have been applying in many applications with sophisticated problems. For example, Arias-Montano et al. (Arias-Montano et al., 2012) documented a complete surveying paper of different applications where MOEAs were deployed for solving multiple issues in aerospace.

II. Genetic Algorithms:

Genetic Algorithms (GA) fall under the category of Nature-Inspired Methods (NIM), alongside other popular techniques such as Particle Swarm Optimization (PSO) or Ant Colony Optimization (ACO). GA has been a well-explored method since the 1960s and has found application in various scenarios. The fundamental concept behind GA is the emulation of evolutionary behavior in nature, specifically the "survival of the fittest." This notion entails that, from an initial population of individuals representing solutions to a given problem, successive generations evolve to produce individuals that are superior or of higher quality compared to those in the initial population (the fittest) (Figure 2.4).

Recent efforts aim to enhance the performance of GA in path planning by introducing new approaches, such as novel solution representations and initial population selection methods, along with improvements to operators like parent selection, crossover, and mutation. For instance, Alnasser et al. propose a suitable solution representation in a grid map environment, coupled with an intelligent crossover operator and a fitness function that considers various criteria for robot motion. This includes minimizing the number of turns to reduce the robot's energy consumption.

Adjustments to GA parameters are suggested to prevent premature convergence, as demonstrated by Karami and Hasanzadeh, who adapt the selective pressure of the selection operator for 2D robot planning. The adjustment is based on the standard deviation of the fitness function of the latest population. The literature on GA parameter adjustment indicates its significance due to the algorithm's application to diverse problems, with performance heavily dependent on these parameters. The authors present a classification according to a conceptual model that divides the process of adapting parameter values into four steps. Notably, the works involving adjustments in mutation, crossover, and population have seen linear growth, while other adjustments, such as parent selection and replacement representation, still receive less attention.

Previous works have primarily focused on static environments. However, a more realistic approach involves considering dynamic environments, where new information about the environment updates as the robot moves. The concept of visible space is utilized to determine paths between two positions in a grid map with obstacles. Visible space involves selecting the next waypoint in a path from a set of feasible points, excluding obstacles. The authors create an initial feasible population and introduce novel mutation operators that correct infeasible paths, allowing the approach to handle obstacles not initially considered.

GA has also been applied to classic Traveling Salesman Problem (TSP) scenarios. For instance, a GA algorithm is employed to find a sequence of charging stations for a fleet of electric vehicles (EV). Another combination of TSP with path planning is explored, focusing on an Unmanned Air Vehicle navigating certain points on the map while avoiding restricted zones, such as enemy radar locations.

In this study, a similar combination of TSP and path planning for autonomous vehicles is applied. Where forbidden zones are considered, this work incorporates regions of interest (ROI) that the Autonomous Surface Vehicle (ASV) should traverse. Additionally, there is an adjustment of the mission objective reflected in the tuning of GA parameters. Table I provides a summarized comparison of some characteristics between this work and related studies (Arzamendia et al., 2019).

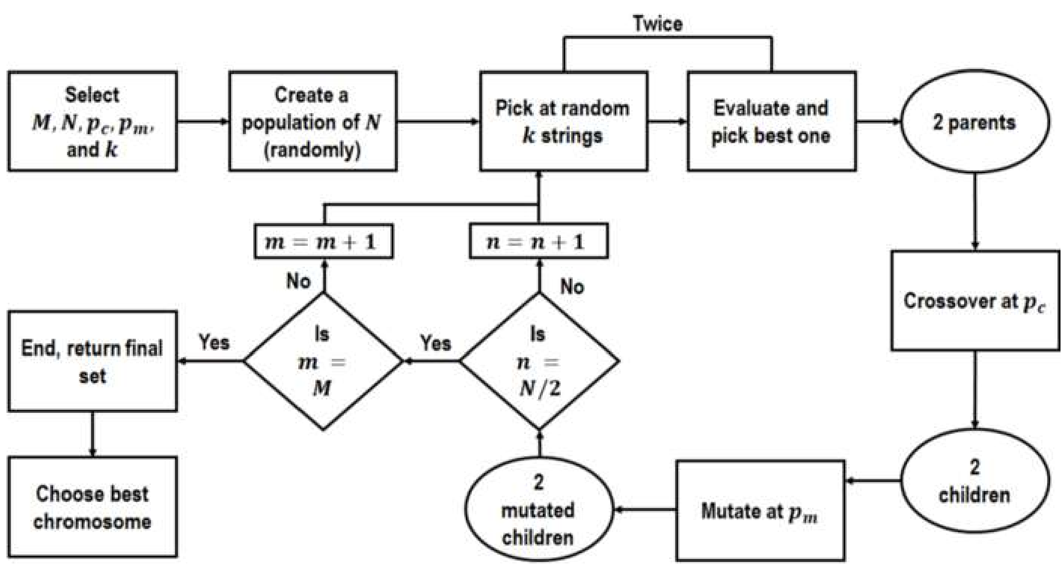


Figure 2.4 Genetic Algorithm (GA): A Simple and Intuitive Guide

III. Multi-Objective Swarm-Intelligence Based Approaches

Systems stimulated from the cooperative behaviour of animals like wasps, birds, bees, ants, termite, and fishes are discussed as Swarm Intelligence Algorithms (SIA) (Talbi, 2009). SIA initiated from the social behaviours of the actual world species that compete for their foodstuffs. The highest physical appearance of SIA is their elements are modest to calculate and simple agents, they cooperate by an unintended internal interaction platform that leads in the decision support systems.

Amongst the SIA stimulated optimization methods artificial bee colony (BC), ant colony (Ac) and particle swarm optimization (PSO) are the best effective approaches in the pedestrian's route planning which will be discussed in next sections.

IV. Artificial Bee Colony Algorithm

The bee colony optimization algorithm is consider as a stochastic P-metaheuristics approach that categorized into the class of SIA. Since the last decade, various educations have been established based on different BC behaviours in order to solve multifaceted continuous improvement issues (Bitam et al., 2008). BC optimization algorithm is motivated by the action of honeybee colonies that shows lots of structures that might be found as models for collective and intelligent behaviours. These structures can be listed as waggle dance, mating through flight, nectar search, food foraging, and separation of labour force. However, BC-based optimization algorithm is mostly developed based on three diverse methods of marriage, nest site search, and food searching in the bee colonies. Each individual model can define a particular action for a detailed assignment (Figure 2.5).

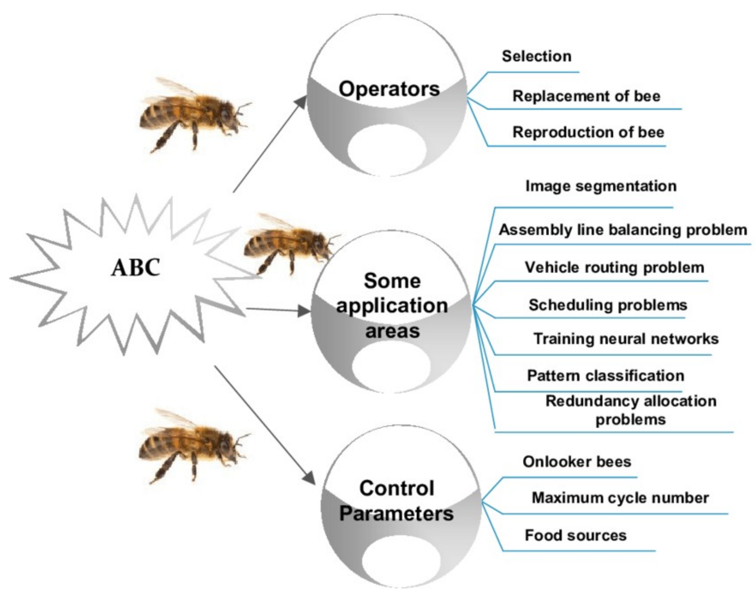


Figure 2.5 Ant Colony Optimization (ACO) algorithm

The new AC algorithm was calculated to explain the constant optimization problem with a single-objective purpose (Karaboga, 2005). In order to overcome a multi-objective optimization problem (MOOP) and switch the discrete multi-objective evacuation model, more or fewer alterations were proposed with respect to AC. A number of researches prolonged the prime AC algorithm in order to address the MOOP (Farahani et al., 2014). A maximum number of these research focused on the practice of Pareto-based methods to enhance the multi-objective difficulties; yet less have investigated on the enhancement of the local-search routine of AC.

Fang et al. (2017) engaged an Artificial Bee Colony (ABC) on multi-objective route planning system for pedestrian navigation at nighttime. They measured three main objectives for their conditional considerations, including, full route length, pedestrian traffic capacities, and functionality of road lights at night. As a result, they adopted several strategies of ABC, containing the restricted neighbourhood searching, the demonstration of the solutions, and the Pareto front calculation technique to adjust the ABC with route planning problems.

V. Ant Colony Optimization Algorithm

The plain thought in ant colony optimization algorithms (ACO) would be to reproduce the cooperative conduct of actual ants to resolve optimization difficulties. ACO metaheuristics have already been suggested by M. Dorigo. They could be viewed as multi-agent system where every single one is motivated by the act of an actual ant. Typically, ACO has already been put on combinatorial optimization difficulties and they contain achieved extensive achievement in resolving unique issues (e.g., arranging, routing, task) (Talbi, 2009).

The foremost curiosity of actual ant's action can be that easy ants applying collective behaviours accomplish complex tasks like for example transportation of meals and locating the shortest pathways to the meal's options. ACO processes imitate the rule that using very easy communication system, an ant colony can discover the shortest route between two details. Figure 2.6 illustrates a test accomplished by Goss et al. (Goss et al., 1989) with a genuine colony of ants. Observe that those ants could not look at perfectly while the colony has got usage of a food resource associated by two pathways towards the colony's nest. Throughout their journeys, a chemical substance trail like pheromone is certainly left on the floor. The pheromone can be volatile and locative elements. The role of the trail would be to direct other ants to the perspective area. The bigger the quantity of pheromone on a specific path, the bigger the possibility that these ants will indicate the path. For a confirmed ant, the road is chosen based on the smelt level of pheromone (Talbi, 2009).

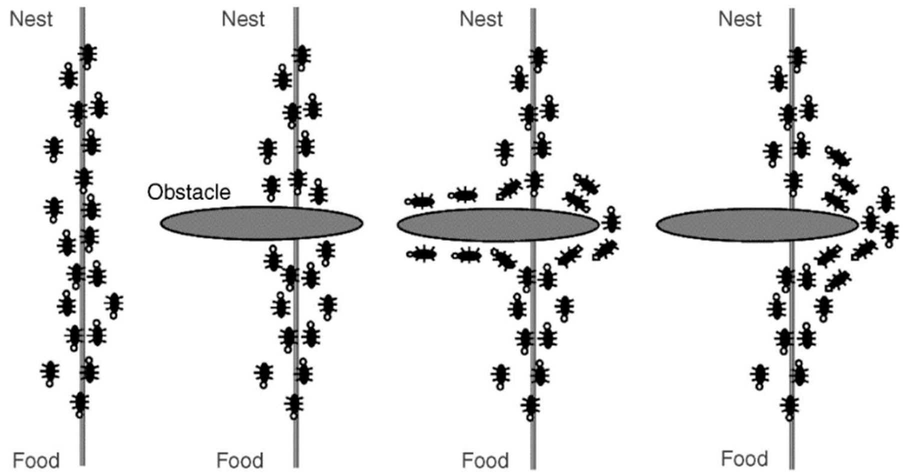


Figure 2.6 Inspiration from an ant colony searching an optimal path between the food and the nest.

There are some academics that have used the ACO for multi-objective path planning applications (Masoumi et al., 2019). They have studied dissimilar strategies to adjust the ACO for optimizing the path planning. For example, (Iredi et al., 2001) suggested a bi-criterion ant colony optimization algorithm to exactly explain a bi-criteria vehicle routing difficulties.

VI. Particle Swarm Optimization

Particle swarm optimization is considered as a stochastic population-based metaheuristic motivated from real-world swarm intelligence (Kennedy, 2006). It imitates the social acts of natural animals like for example fish and birds gathering to discover a particular point with sufficient foods. Undeniably, in these swarms, synchronized behaviours with local actions develops without any principal control function. In the beginning, the PSO has been effectively planned for continuous optimization difficulties (Kennedy, 2010) (Figure 2.7).

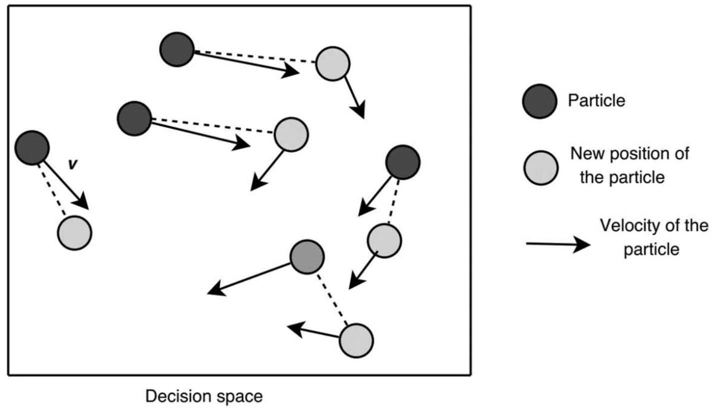


Figure 2.7 Particle swarm with their associated positions and velocities.

At each iteration, a particle moves from one position to another in the decision space. PSO uses no gradient information during the search.

A. Machine Learning Based Decision Making

Calculating routes regarding several criteria make reference to the Multi-objective shortest route problem (MSPP), a principle problem in neuro-scientific multi-objective optimization. Fixing the emerging trouble contains seeking the group of non-dominated journeys that the users decide their most favourite one. Because the Pareto dominance notion, offered two journeys option-A and option-B, it is stated that option-A dominates option-B when there is a minimum of one criterion that option-A includes a less expensive than option-B and there is absolutely no criterion that option-B includes a less expensive than option-A. An optimal journey is subsequently called Pareto-optimal when it's not necessarily dominated by any journey (Dib et al., 2017).

The foremost issues in multi-objective contexts are due to the truth that, in many enhancement issues, determining the complete group of non-dominated solutions is really a time-consuming process since one difficulty may have a wide array of non-dominated alternatives (even yet in situation of two goals). Furthermore, and as opposed to single criteria research, one cannot abort the look for after getting a first optimal answer. Indeed, even with acquiring all Pareto-optima, research algorithms need a substantial timeframe to ensure that no more solutions exist. Thus, in many optimization issues, specifically those necessitating real-time solution, the primary focus isn't on locating the optimal Pareto alternative set. Rather, just about all approaches rest in applying heuristics procedures whereby near-optimal alternatives are usually computed in affordable computational time.

Although there are many machines learning decision-making methods have been designed, implemented and tested yet, the optimal solution cannot be guaranteed. It is known that none of the produced models take over the others.

Basically, machine learning, deep learning, reinforcement learning, and transfer learning approaches can play a significant role on decision support systems especially in multi-objective path problem where the result is multiple probable solutions and there is a huge need to decide which one is the most optimal one. Support vector machine (SVM), convolutional neural networks and boosting regression are some well-known yet highly accurate machine learning methods can be implemented to find the ideal path planning (Figure 2.8).

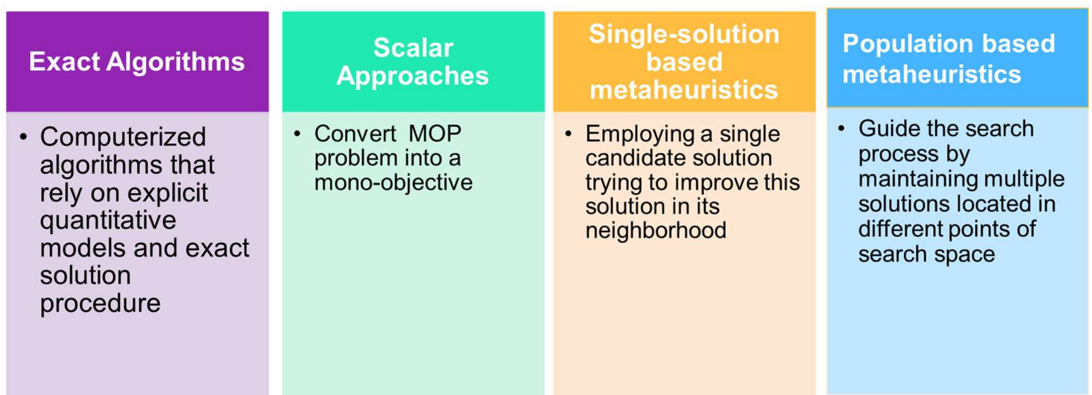


Figure 2.8 Commonly used Algorithms in Pedestrian Route Planning (Pros and Cons)

2.8 Research Gap Analysis and Key Contribution

After an in-depth analysis of the literature, several research gaps were identified in the studies covering critical components of pedestrian route planning systems including:

- Pedestrian Route Choice Quality Parameters
- Computational Algorithms
- Path Selection Decision Making

A summary report of the research gaps, original contributions are articulated as follows.

2.8.1 Pedestrians' Route Choice Quality Parameters

- **Research Gap**

After reviewing 62 relevant studies in finding influencing parameters in pedestrian route planning, we found several issues have not been clarified by the authors in the phase of selecting parameters for developing a route planning framework e.g. using an insufficient number of contributing factors, unclear definitions of the contributing parameters, shallow justification for parameters selection, unreliable justification for selecting the parameters coming from either poor literature, subjective author's experimental mindsets or nearly irrelevant empirical sources, and undefined insight and goal for required parameters matching with the real existing routing problem. Overall, it seems the scientific process of determining the relevant parameters during route planning framework development has been often ignored in the available literature. Moreover, there is no systematic scientific work available articulating which aspects of the main parameter influence the choice of a walking path in pedestrian route planning frameworks.

- **Research Contribution**

To provide a classified insight on main influencing parameters in pedestrian route selection, Chapter 3 of this research, first, provides a critical review of thematic studies to identify the most contributing aspects and related factors in safety, attractiveness, accessibility, and comfort and then systematically categorized each parameter in multiple levels of high-level category, parameter's main aspect, influencing factors and authentic spatial factors. We also discussed the available approaches of parameters selection for pedestrian route planning among multiple case studies. The proposed framework of this research through which the contributing parameters, their spatial aspects, and route selecting approaches are articulated, can be beneficial to direct the pedestrian route modellers to build an optimized/personalized multi-criteria pedestrian route planning.

2.8.2 Computational Algorithms for Pedestrian Route Planning

- **Research Gap**

The selection of right algorithm is a critical challenge in developing an efficient pedestrian route planning framework. Multi-objective pedestrian route planning counts as an NP-complete problem (Garroppo et al., 2010). According to our findings from the literature, different optimization algorithms can successfully be employed in PRP. Literature analysis shows commonly used algorithms in pedestrian route planning falls in the categories of Exact Algorithms, Scalar Approaches, Single Solution based Metaheuristics, Population-based Metaheuristics, and Hybrid approaches from all above mentioned. A summary of available drawbacks in using these algorithms for solving pedestrian multi-objective personalized routing problem explained in the following:

I. Exact Algorithms:

Exact algorithms are computerized approaches that rely on explicit quantitative models and exact solution procedure. As an example in this domain, we can mention two common heuristic-based algorithm for shortest path calculation which are Dijkstra and A* algorithm (Ferguson et al., 2005). These two algorithms effectively give the optimal route for various research route planning problems. For example, route planning method by means of Dijkstra's algorithm for indoor space to navigate blinded users (Wu et al., 2007) and also the fusion of Floyd algorithm and Dijkstra to expand path planning for mobile robot in life science laboratories (Liu et al., 2012). However, there are drawback to these algorithms. They perform well on single-criterion case and are difficult to adapt with multi-objective mode. In other word, they become computationally expensive and incompetent when the dimension of the problem stays large (Chakraborty & Hashimoto, 2010; Medhi & Ramasamy, 2017).

II. Scalar Approaches:

They convert Multi-Objective Problem (MOP) into a single objective using weighting approaches (Fang, Li & Zhang 2011). However, they have some drawbacks. From one side, by converting multi-criteria problem to a simple single criteria problem, the decision maker will certainly loose several interesting solutions, cause problem is not solved in real mode of multi-objective in which all objective functions are optimized concurrently (Yao et al., 2018). From the other side, such methods may become a reason for increasing running time exponentially through the resolution phase of the problem. To be precise, computational time makes these classical approaches impractical in real-world route planning system where pedestrians ask for immediate answers (Dib et al., 2017).

III. Single-Solution Based Metaheuristics:

These metaheuristics generating a single solution while trying to enhance that in its neighbourhood. Improvement applies by transform and manipulation of generated solution throughout the search. These metaheuristics algorithms are exploitation oriented and have the power to intensify the search in local regions (Talbi, 2009). Though, the major drawback of these algorithms can be lack of reaching to global optimum, and it might get trapped in local optimums (Jaddi & Abdullah, 2020).

IV. Population Based Metaheuristics:

Due to defects of exact methods in multi-objective problems, researchers have started to focus on metaheuristics algorithms which can be employ on a wide range of problems (Sörensen et al., 2018). Population Based Metaheuristics direct the search process by keeping several solutions situated in different spots of search space. In population-based algorithms an entire set of solutions is evolved. It famous, these algorithms are exploration oriented and let a better divergence in the entire search area compare to methods in Single-solution based (Talbi, 2009).

According to (Dib et al., 2017) the key motivation behind utilizing metaheuristics in route planning compare to other methods comes from their capability:

- To deliver close optimum solutions in acceptable computational running time.
- Offering flexibilities and high performance to cover a number of optimization categories (Mono criteria, multi-criteria) in dynamic, static or even stochastic modes.
- Produce a reasonable sub-optimal solution in a little time, particularly in multi objective optimization problems.
- Applicable on large-scale or many criteria problems.

V. Hybrid Algorithms:

Numerous techniques have been suggested to ideally compute the multiple non-dominated trips were moving from one location to another one (i.e. Dijkstra algorithm is the most famous one in this field). Nevertheless, these stand-alone algorithms are less efficient or sometimes even inapplicable whenever the number of considered criteria is very critical or the node networks are extremely large. Hence, hybrid algorithms are advisable in such a situation to cover the underestimation/overestimation of the stand-alone models. For example, Dib et al. (2017) proposed an advanced heuristic method whereby the genetic algorithm was integrated with the variable neighbourhood search (VNS) technique in order to solve the multicriteria shortest path problem in pedestrian systems.

- **Summary**

Nowadays, industrial practitioners and researchers usually focus on the technology and theory of locating and directing pedestrians, and frequently provide shortest-path solutions (Fang et al., 2017; Hashemi & Karimi, 2017) with consideration of one or two criteria (Yao et al., 2018). Numerous pedestrian navigation systems yet implement the methods hired in car navigation systems and apply their approaches which are not suitable for planning systems for pedestrians (Gartner et al., 2011). In case of considering multiple criteria, often, all objectives converted into a single objective using weighting approaches, in this condition, the problem is not solved in real mode of multi-objective, in which all objective functions are optimized concurrently, and this leads to losing a number of interesting solutions and can extend the runtime exponentially (Fang et al., 2017; Talbi, 2009). As a result, the need to use metaheuristic population-based methods in multi-objective routing problems as NP-hard problems is critical in the future research (see Table 2.2).

Table 2.2 Synoptic table include related works and research gap.

Reference	Core Activity	(Mono Bi Multi) Criteria	User-Centric Preferences (Yes / No)	Context Awareness (Yes / No)	Method (Single Solution/Population Based)	Scale (Small/ Large)	Time Efficient (Yes/ No)	Decision Making (Offering Final Best Route)
(Rahaman et al., 2017b)	Contour-based accessible path routing	Bi-Criteria	to some extent	to some extent	Population Based (A* algorithm)	Small Scale	Yes	No
(Pahlevani et al., 2019)	Multi-Modal Multi-Criteria Personalized Route Planning	Bi-Criteria	Yes	No	Population Based	Small Scale	Yes	No
(BOZKURT KESER et al., 2016)	personalized Route Planning (least cost path)	Multi-Criteria (4)	Yes	No	Single Solution Based (Weighting A* algorithm)	Small Scale	No	Yes
(Pingel, 2010)	Route prediction with slope consideration (least-cost path)	Single-Criterion	to some extent	to some extent	Single Solution Based	Small Scale	No	Yes

- **Contribution of this Research**

Considering that we have a multi-objective optimization problem with conflicting objectives, one of the best solutions is using a metaheuristic population-based algorithm where all possible solutions considered, generated, and evaluated by the algorithms simultaneously. Therefore, in this research, we employed a novel metaheuristic Swarm-Intelligence Based Approaches approach, namely Pareto-Based Multi Objectives Ant Colony Optimisation (PB-MOACO), capable of considering multiple objective functions simultaneously (Doerner et al., 2004). This algorithm designed for multi-objective optimization problems and never been used to solve multi-objective route planning problem for pedestrians.

2.8.2.1 Rationale Behind Selecting PB-MOACO for Multi Objective PPRP

In developing our multi-objective personalized pedestrian route planning system, we have chosen the **Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO)** algorithm for our multi-objective pedestrian route planning framework. This decision is grounded in a comprehensive evaluation of various optimization methodologies (discussed in previous sections), considering factors such as problem nature, computational efficiency, and algorithmic complexity. In addition, PB-MOACO 's ability to effectively balance multiple conflicting objectives—accessibility, safety, attractiveness, and comfort within a graph-based routing context —while efficiently navigating the discrete and connectivity-constrained nature of urban pedestrian networks is another key factor in selecting this algorithm. The following sections detail the key reasons for selecting PB-MOACO over alternative approaches.

1. **Nature of the Problem**

Urban pedestrian route planning is inherently a graph-based problem, where the environment is represented as a network of nodes (intersections) and edges (pathways) (Kielar et al., 2018). This discrete and connectivity-constrained structure aligns well with the PB-MOACO framework, which excels in navigating complex graph topologies to identify optimal paths. The algorithm's design inherently accommodates the multi-objective nature of the problem, allowing for simultaneous optimization across multiple criteria without the need for scalarization.

Considering the problem's nature, the need for computational efficiency, and the challenge of balancing multiple objectives simultaneously, PB-MOACO clearly outperforms alternative approaches. Its ability to provide a well-balanced set of Pareto-optimal solutions, coupled with efficient convergence and adaptability, makes it the ideal choice for our multi-objective pedestrian route planning application (Chau & Gkiotsalitis, 2025).

2. **Comparison with Alternative Algorithms**

- Unlike weighted aggregation (scalar) methods—which require a priori assignment of weights and may not capture dynamic trade-offs effectively (Iredi et al., 2001)—PB-MOACO naturally generates a diverse Pareto front, allowing for adaptive selection of optimal routes without imposing rigid, subjective criteria.
- Exact algorithms, while guaranteeing optimality, tend to suffer from exponential computational complexity when applied to large-scale urban networks, making them impractical for real-time or large-scale pedestrian routing (Cormen et al., 2009). In contrast, PB-MOACO leverages the iterative, pheromone-based learning mechanism of Ant Colony Optimization to efficiently explore complex, multi-dimensional search spaces, ensuring rapid convergence to high-quality solutions (Dorigo & Stützle, 2004).
- Moreover, PB-MOACO is highly parallelizable, allowing for efficient execution on modern multi-core systems (Cazenave and Jouandeau (2007) —a crucial advantage when processing complex urban network data.
- While hybrid algorithms may combine the strengths of different methods, their increased complexity and integration challenges often impede scalability and ease of implementation. In contrast, PB-MOACO maintains a relatively straightforward implementation (Hussin & Saifullah, 2015), making it easier to calibrate and fine-tune specifically for urban pedestrian routing challenges. This simplicity, combined with its effectiveness in balancing multiple conflicting objectives (accessibility, safety, attractiveness, and comfort), establishes PB-MOACO as a particularly suitable and efficient choice for our multi-objective pedestrian route planning application.
- Furthermore, compared to population-based metaheuristics like Evolutionary Multi-Objective Algorithms (EMOAs) (Deb, 2001), which often demand extensive parameter tuning and significant computational resources, PB-MOACO offers a more targeted and robust search framework tailored to the discrete, connectivity-constrained nature of urban pedestrian networks. PB-MOACO

leverages the inherent positive feedback mechanism of pheromone trails, which helps to quickly reinforce promising solutions and accelerate convergence even in large-scale network environments. Additionally, its iterative approach is naturally adaptive, dynamically adjusting search strategies based on real-time feedback, which minimizes the risk of premature convergence and improves the overall quality of solutions.

3. Advantages of PB-MOACO

- **Efficient Exploration and Exploitation:** PB-MOACO utilizes pheromone trails and heuristic information to balance exploration of new paths and exploitation of known good solutions. This mechanism enables the algorithm to efficiently converge towards high-quality solutions without exhaustive searches (Dorigo & Stützle, 2019).
- **Dynamic Adaptation:** The algorithm adapts to changes in the environment or objective functions dynamically, making it robust in real-world scenarios where urban conditions may vary. This adaptability ensures that the generated routes remain optimal even as the underlying network changes (Shan et al., 2024).
- **Computational Efficiency:** Compared to other metaheuristics, PB-MOACO has demonstrated competitive performance with relatively lower computational requirements. Its iterative nature allows for progressive improvement of solutions, making it suitable for large-scale applications without prohibitive computational costs (Iliopoulou et al., 2019).
- **Simplicity and Scalability:** The algorithm's structure is straightforward, facilitating ease of implementation and scalability to larger networks. Its modular design allows for seamless integration of additional objectives or constraints as needed (Zhang et al., 2017).

In summary, PB-MOACO offers a robust, efficient, and adaptable framework for multi-objective pedestrian route planning in urban environments. Its alignment with the problem's graph-based nature, coupled with advantages over alternative algorithms in terms of computational efficiency and solution quality, makes it a superior choice for our application.

2.8.3 Path Selection Decision-Making

- **Research Gap**

Lack of considering pedestrians heterogeneous groups with having various levels of physical abilities, personal preferences, varieties of conditions and real needs are amongst the main drawbacks of current pedestrian navigation services (Appolloni et al., 2019; Bao et al., 2017; Caros & Chow, 2020; da Silva et al., 2020; Fang et al., 2017; Galbrun et al., 2016; Hashemi & Karimi, 2017; Rahaman et al., 2017b; Yao et al., 2017). Moreover, lack of decision-making strategies during the use of many-objective optimization algorithms to conclude an optimal route recognized as another shortcoming in this area.

- **Contribution of this Research**

Designing a decision-making strategy by:

- Applying the user preferences where different groups of pedestrians interactively define the weights of their priority factors based on their preferences in different situations.
- Developing a ranking approach to select the best solution among Pareto-optimal.

2.8.3.1 Rationale Behind Applying Post Optimisation as Decision Making Process

Applying post-optimization—that is, selecting a single final solution from the Pareto-optimal set based on user preference weights—offers several key benefits:

- Personalized Decision Making: Post-optimization allows for the integration of user-specific preferences after the multi-objective search is complete. This means that the decision-maker can adjust weights dynamically to reflect their current priorities without affecting the integrity of the optimization process (Deb, 2011).
- Flexibility and Efficiency: By decoupling the preference articulation from the search process, the algorithm does not need to be re-run when user priorities change. This separation simplifies the decision-making phase and reduces computational overhead, as only the final selection is influenced by user input (Miettinen, 1999).

- Enhanced Usability: Presenting a single, well-ranked solution rather than an entire Pareto front minimizes decision fatigue and provides a clear recommendation for end-users. This approach aligns better with real-world scenarios where users often prefer a single, actionable option rather than having to choose among multiple alternatives (Eckart Zitzler et al., 2000).

These justifications support the use of post-optimization in our multi-objective pedestrian route planning system, ensuring that the final route not only reflects an efficient balance among conflicting objectives but also aligns closely with individual user needs.

2.9 Summary Contributions of this Research

1. Developing hierarchical taxonomies on influential route choice quality parameters for pedestrians in four main categories of Accessibility, Attractiveness, Safety and Comfort (Details provided at Chapter 3)
2. Proposing novel personalised multi-objective pedestrian route planning problem (Details provided at Chapter 4)
3. Developing novel personalised pedestrian route planning system considering multiple interconnected essential components (Details provided at Chapter 5.2 to 5.6)
4. Designing Pareto-Based MOACO to generate multiple pareto front solutions based on four different conflicting objectives (Details provided at Chapter 5.6).
5. Designing post-optimisation function help applying the user preferences based on four different factors on pareto front solutions and reach to one final optimised last solution (Details provided at Chapter 5.5.3).
6. Testing route planning scenarios in real-world network of City of Sydney and compare results with two benchmark algorithms (Details provided at Chapter 6).

CHAPTER 3

HIERARCHICAL TAXONOMIES ON INFLUENTIAL ROUTE CHOICE QUALITY PARAMETERS FOR PEDESTRIANS

3.1 Introduction

Walking is the most environmentally friendly mode of transport. Walking on a footpath, the simple, everyday act of pedestrians commuting, exercising or just out for pleasure, has attracted its area of abundant research. In a world where pedestrians are increasingly dependent on e-navigation systems, what factors influence these wayfinding decisions?

In recent years, navigation systems have rapidly taken on the roles of application to essential parts of everyday life. In the meantime, pedestrian navigation has developed into an important practical and theoretical research subject in numerous location-based disciplines such as cartography, geographical information science, indoor and outdoor positioning, and spatial behavior in sociology, neuroscience, and psychology (Fang et al., 2015). Pedestrian navigation emphasizes how to effectively and efficiently design a route's guidance from origin to destination (Wang, 2018).

As with car "Sat-nav", pedestrian navigation systems usually consist of the three standard modules of route positioning, route planning and route communication/presentation (Huang & Gartner, 2009). Positioning registers the pedestrian's location using GPS. Route planning involves calculation of the pedestrian's desired route from origin to destination. The route communication module for pedestrian physically presents and visualizes semantic route instructions enriched with landmarks in various forms such as audio, visual, 3D, hybrid, haptic, and augmented reality (Gartner et al., 2011).

Route planning which is the key module of any navigation system has an important role in real-world applications such as transport systems, communication networks, space applications, autonomous robotics, military guidance and energy (Dib et al., 2017). It is also a broadly considered topic at intelligent transportation in pedestrian navigation services (PNS).

Quality parameters are influential quality factors in route selection by pedestrians. They refer to any factors that are determinative in the selection of the path by the user (Seneviratne & Morrall, 1985). Pedestrians have dissimilar preferences while choosing a specific route to a particular destination. Parameters required for pedestrian route planning (PRP) are relatively different from those of car navigations. While vehicle drivers strongly desire the quickest or shortest route, pedestrians, especially if they have sufficient time, interested in better-quality routes, prefer more straightforward, convenient, safer, or just more scenic routes (Golledge, 1995).

Among all necessities for developing any form of pedestrians' route planner, e.g., systems, algorithms, or frameworks, selecting proper route choice quality parameters and relevant decision variables has been always a critical subject.

Although a wide range of PRP studies has considered various route choice quality parameters, yet there has been no comprehensive study reviewing the parameters and authentic aspects classified into appropriate categories. Moreover, the lack of clear insight into scientifically or logically selecting parameters in PRP studies has led to various ambiguities in this area over the years. To overcome these challenges, this study reviews prior studies in pedestrian route recommendation systems that focus on solving pathfinding problems in one or more of the four challenging domains: safety, accessibility, attractiveness, and comfort. To do this, we first review various considered aspects of mentioned quality parameters (involved in pedestrians' route selection) and discuss the authors' points of view in each category. We then propose hierarchical taxonomies covering multi-levels of decision variables including authentic spatial aspects at each class.

The reminder of this review article is structured as follows: Section 2 gives an overview of the research methodology. Section 3 provides the results reviewing main high-level route quality parameters and considered aspects adopted in PRP systems in four categories of safety, accessibility, attractiveness, and comfort, respectively. Section 4 dedicated to discussion covering key findings in each category. We present multi-level aspects of main parameters identified in our survey through the SACA taxonomy and discuss the attributes and characteristics of each parameter in details. Limitations of the study also covered by this section. Afterwards and in section 5, we provide the conclusion and propose future directions for research related to pedestrian route quality parameters.

3.2 Research Method

The route choice quality parameters employed for pedestrians' route planning (PRP) systems analysed using a systematic review approach in this research. A systematic literature review evaluates, identifies, and interprets all related studies relevant to specific research questions. The necessity for such a review resulted from the requirement of academic researchers and industrial developers to compile and systematically categorize all current info about some phenomenon in a structured manner (Keele, 2007).

The standard guidelines for systematic reviews related to the outdoor navigation systems cannot be adopted directly in this study. Categorizing various quality parameters and variables for PRP systems is an interdisciplinary task between pedestrians' preferred criteria in four domains of safety, accessibility, attractiveness, and comfort. Therefore, the review protocol follows the designed guidelines and point of view of the authors in this domain. All the authors agreed upon amendments to the protocol during the review. The review method developed as shown in Figure 3.1.

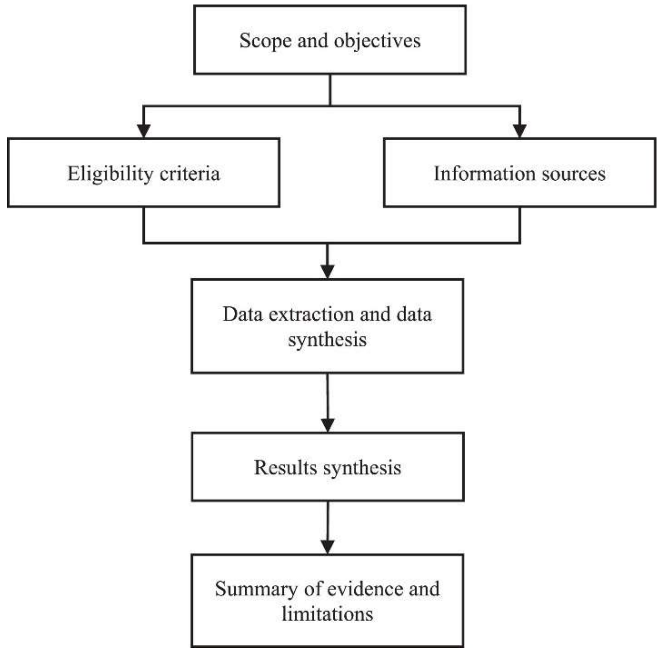


Figure 3.1 Plan of research review methodology and main components

3.3 Research Questions

The following elements suggested by Kitchenham et al. (Brereton et al., 2007) are used to derive the research questions:

- **The population**: route planning systems for the pedestrians as end-users.
- **The intervention**: route choice quality parameters and relevant spatial variables.
- **The outcome**: hierarchical classifications on influential route planning quality parameters for pedestrians.

The review questions for this research formed as:

- RQ1– What are the high-level route quality parameters adopted in PRP systems?
- RQ2 – RQ5 Which aspects of the Safety/Accessibility/Attractiveness/Comfort factor have been considered in PRP studies?

Moreover, to all the last four above: Are there relationships between various considered aspects (by authors) in each domain?

- What are the logical and systematic/hierarchical classifications for these parameters and variables at each category?

3.4 Scope and Objectives

The scope was the systematic review of quality parameters adopted in thematic PRP studies. The objectives of this review are first; to identify high-level route quality parameters and recognised aspects implemented in PRP studies, and second; to find the relationship between reported aspects in each domain and, third to structure them as hierarchical order categories.

3.5 Information Sources

The articles related to the topic come from different disciplines including computer vision, computing, engineering, and pedestrians' behaviour studies. The sources are selected from electronic online databases of Web of Science (www.isiknowledge.com), Scopus (www.scopus.com), and Google Scholar (www.scholar.google.com).

3.6 Eligibility Criteria

A series of standards covering inclusions and exclusions criteria were applied to find studies participating in the determined objectives.

The inclusions are as follows:

- Published in English
- Published between 2000 and 2021
- Issued in peer-reviewed journals or conferences
- Discussed pedestrian route-choice influential parameters
- Concentrated on route guidance of pedestrian navigation covering parameters' definition.
- Discussed approaches for determining parameters including surveying techniques.

The exclusion criteria include:

- Studies focusing on car-route planning.
- Absence of explicit definitions of parameters
- Lack of discussing parameter selection approach.

To check eligibility, the authors evaluated the titles, keywords, abstracts, parts of the methodology, discussion, and conclusion.

3.7 Search Terms and Strategies

To acquire the relevant papers, keywords for a comprehensive search were identified based on a preliminary search in route quality parameters in pedestrian navigation systems and route planning where suggested related terms can be discovered. The identified keywords and synonyms are planned in Table 3.2.

Table 3.2 Keywords and synonyms used in the search strategy formulation.

Keyword	Synonyms
Pedestrian route-planning	Routing model, wayfinding
Parameters in pedestrian navigation systems	Pedestrians Route Choice Criteria, Route Quality Parameters
Pedestrian-related issues/concerns during path finding	Safety, Accessibility, Attractiveness, Comfort

3.8 Data Extraction Process and Selected Studies

Data extraction process was based on preferred reporting items for systematic reviews and meta-analyses (PRISMA) Statement proposed by Moher et al. (2010).

Following the research methodology, we initially obtained 753 articles, of which 427 papers were selected according to the eligibility criteria and eligible for full paper selection. From the eligible articles, 97 were selected for the analysis. The data extraction procedure developed based on (Moher et al., 2010) and illustrated in Figure 3.1.

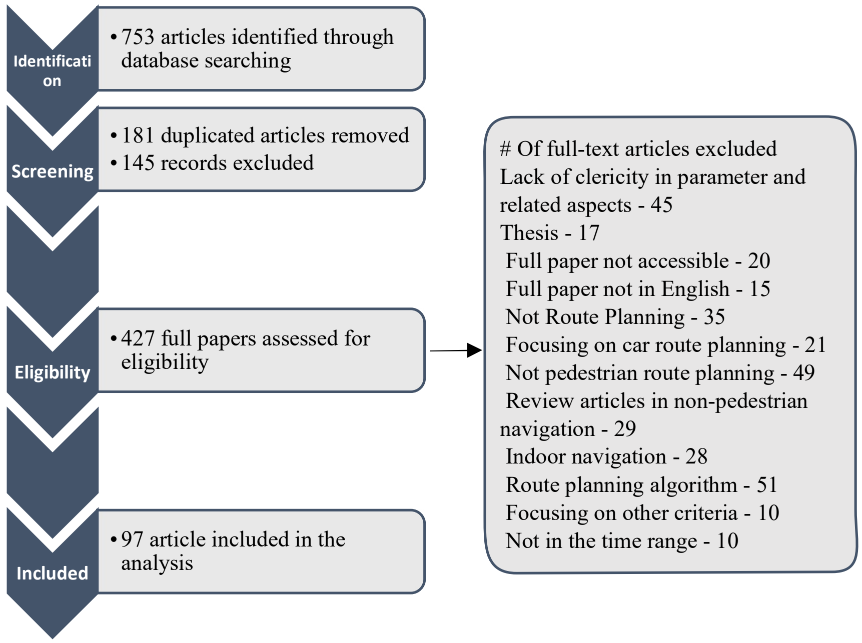


Figure 3.1 Flowchart of the article selection process

3.9 Data Analysis and Synthesis

Extracted data is used to answer the research questions using qualitative synthesis methods. Data analysis and writing of the manuscript were done by the first author. Both second and the third author reviewed the manuscript.

3.10 Results

3.10.1 RQ1 - Main Route Quality High-Level Parameters Adopted in PRP Systems

Table 3.3 summarizes the articles with article references and present the distribution of the studies in four areas of safety, attractiveness, accessibility, and comfort. Apart from reviewing case studies, we discuss various considered aspects by authors in following sections.

Table 3.3 Summary of main considered parameters PRP studies

Domain	Article Reference
Safety	(Wan et al.),(Tiwari, 2020),(Schwarz et al.),(Völkel & Weber, 2008),(Galbrun et al., 2016),(Fang et al., 2017),(Yao et al., 2017),(Yao et al., 2018),(Keler & Mazimpaka, 2016),(Bao et al., 2017),(Miura et al., 2011),(Soni et al., 2019),(Rigolon et al., 2018),(Koryagin et al., 2018),(Garvey et al., 2016),(da Silva & da Silva, 2020),(Appolloni et al., 2019),(Asadi-Shekari et al., 2015),(Singh & Sciences, 2016), ,(Caros & Chow, 2020),(Sahelgozin et al., 2015),(Opach et al.), (Corazza et al., 2020),(Barmpas et al.),(Bukhtoyarov et al., 2020),
Accessibility	(Hashemi & Karimi, 2017),(Sobek & Miller, 2006),(Rahaman et al., 2017b),(Yusof et al., 2015),(Yu et al., 2003),(Kasemsuppakorn & Karimi, 2009),(Qin et al., 2018),(Karimi, 2016),(Karimi, 2018),(Neis & Zielstra, 2014),(Völkel & Weber, 2008),(Grachek, 2021),(Sevtsuk et al., 2021),(Sevtsuk & Kalvo, 2021),(Gharebaghi et al., 2021),(Barmpas et al.),(Sinagra & Solutions, 2020)
Attractiveness	(Cambra et al., 2012),(Ujang, 2013),(D'Acci, 2019),(Novack et al., 2018),(Huang et al., 2006),(Alivand & Hochmair, 2013),(Naharudin et al., 2017),(Adkins et al., 2012),(Cambra et al., 2012),(Gavalas et al., 2016),(Gavalas et al., 2017),(Kachkaev & Wood, 2013),(Appolloni et al., 2019),(Quercia et al., 2014),(Ludwig et al.),
Comfort	(Mölter & Lindley, 2015),(Weber),(Huang et al., 2014),(Bivina & Parida, 2020),(Nahar et al., 2019),(Liu et al., 2020),(Guo & Loo, 2013),(Moura et al., 2014),(Z. Wang et al., 2020),(Shatu et al., 2019),(Gartner et al., 2011),(Peng et al., 2020),(Nurminen et al., 2020),(Grachek, 2021), (Pilipenko et al., 2021),(Deilami et al., 2020)
Other domains	(Al-Widyan et al., 2017),(Monreal et al., 2016)

3.10.2 RQ2 - Safety Aspects in PRP Studies

Safety is one of the critical criteria for improving the quality of the proposed route in pedestrian route planning systems. In this section we reviewed several case studies that employed safety-related factors from a particular perspective in their proposed route planning systems.

To improve convenience and safety, Miura et al. (2011) concentrated on lighting in side streets to provide as short and bright a route as possible in the dark. They established a system that recommends pedestrian routes taking account of street distance and the light intensity detected by wireless network devices. Their results showed the brightest route selection is 20% longer than the shortest route for the same origin and destination.

By combining OpenStreetMap network data, governmental open source properties data and historical crime, Keler and Mazimpaka (2016) proposed a safety index at night for Los Angeles (LA) streets and roads. They selected streetlights, police stations, highway points and crime as influential safety parameters in routing and testing the model. They weighted graph network by safety index and applied obstacle polygons including historical crime hot spots. By comparison and evaluation between the shortest path and the 'safest' path without and with consideration of the crime obstacle polygons, they highlighted the important role of the crime parameter in the generation of varied safest routes.

With the aim of developing a user-centric framework, inspired by Maslow theory, Fang et al. (2017) examined the psychological safety necessities of pedestrians at night, particularly their requirements for lighting, psychological security and comfort. The College of Information Sciences at Wuhan University served as a study area. In addition to route distance, they integrated road illumination and pedestrian traffic volume into proposed pedestrian navigation services. According to their work, these two parameters are observable criteria at night in real route-planning applications. In the presented method, the sense of pedestrian psychological safety at night counted as significant as other objectives, like total route distance. They suggested that pedestrian amenities include sidewalks, warning signs at intersections, reflectance of the environment and road colours are the safety factors that can be considered as possible additions to pedestrians' route-planning systems.

With the equal purpose of calculating safe routes during the night, Bao et al. (2017) evaluated the positive or negative impacts of five factors on route safety and comprehensiveness in the day and at night. They selected lighting condition, landmark visibility, landmark scarcity, width and turning as examination parameters. Their results suggested that longer path had a lesser negative effect on pedestrians' fear of darkness if clear and enough navigational information such as proper illumination and salient landmarks were available.

Sahelgozin et al. (2015) suggested a multi-criteria route-optimization approach for the purpose of providing a Ubiquitous Pedestrian Way Finding Service (UPWFS) for pedestrians in one of the local districts in Tehran. In the introduced framework, the parameter of safety is classified into two parts: Accident Safety and Social Safety. Accident Safety is defined as the safety of pedestrians, considering the probability of an accident with a vehicle while crossing streets. They considered the availability of pedestrian crossing and medical centres in the route segments as Accident Safety subfactors. Social Safety introduced the security of pedestrians and the probability of being attacked or disturbed by an offender. Availability of lighting and police stations are considered as safety factors. They concluded these two categories are not similar and not affected by the same agents.

Galbrun et al. (2016) developed an application aiming to define short and safe paths for pedestrians in the navigation of the major cities of Chicago and Philadelphia. Two aspects of public safety in terms of crime and distance were considered. By integration of algorithmic solutions and an urban-risk model using public data sources of crime, they obtained an application, which helped people to navigate their urban areas securely.

Yao et al. (2017) and Yao et al. (2018) proposed a Reinforcement Learning based Multi-Objective Hyper-Heuristic (RL-MOHH) plan for pedestrian route-planning in smart city. They chose two parameters of safety: routes' crime potential and distance to determine optimized safe walking route. They considered the safety index in navigational services and conducted experimentations on the safety index map, according to the historical crime data of New York City, US. They found the crime risk rises significantly along the path later in the day.

3.10.3 RQ3 - Accessibility Aspects in PRP Studies

According to Alfonzo (2005) Accessibility can be defined as the needs of pedestrians to reach their destination considering both overall travel distance and potential obstacles to walking. Accessibility factors in wayfinding can be attributed to two groups of pedestrians: Able-bodied people and those who are physically disabled. Most of the studies about the accessibility factors on pedestrians' wayfinding approaches have been conducted on people with disabilities rather than able-bodied people. In this section, we explain the major aspects of Accessibility factors for people with different physical abilities including those with special needs (i.e., disabled or wheelchair users, visually impaired, and elderly persons).

During a study conducted by Seneviratne and Morrall (1985), in the summer of 1982, factors affecting the choice of route by pedestrians in downtown Calgary, Alberta was evaluated. From a total number of 2900 interviews on nine successive working days, they garnered 2685 questionnaires eligible for analysis. According to their result, most people chose the shortest way and length should be count as the main consideration during developing and designing pedestrian route planners. Therefore, distance is the main and essentially the primary considerable Accessibility parameter in pedestrian navigation services and studies. It worth mentioning that sometimes the shortest route and the most accessible one might be different. For example, the shortest route might contain severe elevation changes, making it less appropriate for some users while most accessible route can be longer (Hashemi & Karimi, 2017).

In addition to a shorter distance, different characteristics and subsequently various factors can attribute to the Accessibility of the path for pedestrians. These factors can be both factors that facilitate pedestrian traveling and improve the accessibility of the track. We entitled them as Path Facilitators (PF). And factors disrupt or decelerate the ease of the route, introducing them as Path Disruptors (PD). According to relevant literature, PF parameters include: shorter distance, the presence of sidewalks (Jonietz, 2016; Kaufmann et al., 2010; McCormack & Shiell, 2011; Neis & Zielstra, 2014; Sallis et al., 2012; Sugiyama et al., 2012; Van Holle et al., 2012), appropriate street crossing facilities (Borst et al., 2008; IRVIN, 2008; Kaufmann et al., 2010), appropriate street accessibility facilities (Handicap Parking, Handicap Entrance) (Sobek & Miller, 2006), accessibility street furniture (Lighting, Tactile Paving, Stairs, Ramp, Handrail, mobile obstacles e.g. street parking, and sign boards, presence of eaves and roofs) (Inada et al., 2014; McCormack & Shiell, 2011; Neis & Zielstra, 2014; Sobek & Miller, 2006), curb cuts (Sobek & Miller, 2006), proper surface structure (Hashemi & Karimi, 2017; Karimi, 2018; Neis & Zielstra, 2014), lack of obstructions (Samarasekara et al., 2011) and Pedestrian overpass (Sahelgozin et al., 2015).

Furthermore, some road features, like a longer distance, a path with steep slope or severe elevation variations (Beale et al., 2006; Borst et al., 2008; Czogalla & Herrmann, 2011; Hashemi & Karimi, 2017; Jonietz, 2016; Karimi, 2018; Kasemsuppakorn & Karimi, 2009; Neis & Zielstra, 2014; Pingel, 2010; Rahaman et al., 2017a; Sahelgozin et al., 2015; Sobek & Miller, 2006), human traffic (Hashemi & Karimi, 2017; Karimi, 2018; Kasemsuppakorn & Karimi, 2009; McCormack & Shiell, 2011; Sugiyama et al., 2012; Van Holle et al., 2012), poor surface conditions, obstructions, narrow sidewalks, lack of curb cuts or lack of ramps (Hashemi & Karimi, 2017), physical barriers in sidewalks (e.g. stairs), natural features (mostly in rural paths like a gully), or even psychological barriers

(Alfonzo, 2005) can count as Path Disruptors for pedestrians, especially those with different physical abilities and special needs.

3.10.4 RQ4 - Attractiveness Aspects in PRP Studies

Route planning for recreational leisure walking is very common, especially for tourists. Tourists usually appreciate walking in pedestrian areas, market and urban zones or areas with cultural, architectural and scenic value compared to only viewing sites with limited access or choosing the fastest way to get around the city's sights (Gavalas et al., 2017).

Recreational walking, unlike functional walking, means a more sophisticated combination of parameters that constitute the choice of a specific pathway, many of which have a psychological nature, associated with richer understanding of the area (Davies et al., 2012). In addition, there is a considerable difference between recreational walks in rural and urban areas. Rural sidewalks are mostly designed for recreational walking, but the urban network footpaths are generally functional in nature. Therefore, potential automation of selecting scenic routes in cities becomes a more complicated task (Kachkaev & Wood, 2013).

In the remainder of this section, we review studies that examine the scenic parameters of the path, applied aspects, scenic-based data sources, and overall pleasantness.

Adkins et al. (2012) described and assessed a research approach that used a responsive, surveying-based method and the environmental-based audits to investigate how individual factors of built environments (i.e., the physical features of route section or urban blocks) contribute to the attractiveness of a walking space. The study area consists of four sub-regions within Portland city, USA. Their findings confirmed that well-made green streets, pedestrian network connectivity, parting from transport traffic, ‘bounded openness’ and parks, work together to contribute to the attractiveness of a walking path. They also found route sections on arterial streets convenient to shops have lesser attractiveness walking grades.

Huang et al. (2006) proposed a solution for the multi-objective route-planning problem for tourists, involving nineteen tourist areas in central Singapore. Along with three parameters of operating cost, safety and travel time, the factor of circumambient scenic view quality as one of the main effective criteria in tourist sightseeing itineraries considered in their study. The first criteria were visual exposure, which approximated how visible were certain locations in the landscape. The second parameter known as scenic preference and was basically a quantity of what tourists prefer to see more.

Gavalas et al. (2017) proposed a context-aware mobile urban guide, which they designed as personalized tour-scheduling services app. It empowered tourists to integrate attractive walking routes with individual points of interest in Athens, Greece. The app used the market assets as well as cultural, natural, historical and architectural scenic parameters of Athens' tourist destinations. Their scenic datasets comprised 18 scenic routes, 100 hotels and 113 attractions' point of interests (POIs). POIs categorized in classes of art galleries, museums, parks, squares, archaeological sites, religious heritage and churches, landmarks, and monuments. They categorized attractive routes into market areas, scenic neighbourhoods, historical tours, architectural tours, nature and seaside.

Wan et al. (2018) proposed a hybrid ensemble approach to creating smart route recommendations for tourists in the city of Beijing, China. Weather conditions, seasonality and temperature were selected as determinant factors of the model while Tourists' location scenic spots define as attractiveness parameter. Geo-tagged Flickr photos of Beijing served as a scenic data source. They concluded that the popularity of attractions factors varied in different environments, as tourists are keener to visit scenic locations on warm and sunny days. Besides, in the high season, the appeal of these attractions is considerably more than in the low season.

Quercia et al. (2014) intended to produce automatically routes that were not only short but being pleasant emotionally as well. By relying on a crowd-sourcing platform (urbangems.org), they assessed pictures from streets regarding related happiness, quietness, and beauty.

Naharudin et al. (2017) proposesed a framework for quantifying the attractiveness of FLM (first/last mile) of the entire pedestrian journey in a central area of Kuala Lumpur, Malaysia. They employed Mobile GIS thechniques for gathering spatial pedestrian information on the ground by exploiting existing mapping mobile applications. Four main parameters of signage, food and beverages, resting points, and shelter/shade served to quantify their attractiveness to pedestrians. The results showed the stations with the highest number of built environments and more desired built environments demonstrate greater attractiveness than a station with fewer or less desirable built environments.

The overall pleasantness of a route as another aesthetic aspect is the next determinant parameter impacts the choice of the route by pedestrian (Lloyd, 1992). With an aim to provide an overall pleasant route, Novack et al. (2018) presented a system which creates personalized pleasant pedestrian routes based on OpenStreetMap spatial data. Their system allowed users to determine to what degree they prefer the path to involve social places (restaurants, cafes, shops, etc.), green areas (e.g., squares, trees, parks), and quieter streets (e.g., less traffic). They proposed how the sociability, quietness, and greenness parameters are quantified and estimated from OpenStreetMap data and how they are combined into a cost function of routing.

They concluded and defined a pleasant route as the one with having social places, greenness, and lower traffic noise.

3.10.5 RQ5 - Comfort Aspects in PRP Studies

According to Alfonzo (2005) comfort is attributed to a person's level of convenience, contentment, and ease during walking. A pedestrian's consent with comfort for walking is probably either influenced by the quality of the environment that makes for easier walking or eliminates distressing factors. Researchers have related several factors to pedestrian comfort in wayfinding. For instance:

Alfonzo (2005) classified the quality parameters that may affect levels of comfort into:

- Urban rules, which influence relationship between traffic and pedestrian comfort (e.g., traffic calming policies, the width and length of streets, speed limits, and the occurrence of buffers).
- The sidewalk condition, (e.g., maintenance of sidewalk, sidewalk widths)
- Urban features deliberated to shield from undesirable or extreme weather conditions, (e.g., arcades and canopies)
- Features that supply facilities all over a city. (e.g., drinking fountains, street benches, and other types of street furniture).

Ausserer et al. (2010) took a different view, and focused on the main problems which effect pedestrians' comfort and summarised them as:

- Lack of resting and convivial places
- Inappropriate air quality
- Insecure social places
- Lack of public facilities (toilets)
- Lack of weathering protection facilities
- Improperly illuminated sidewalks.
- Lack of signs and guiding information for visually impaired people

Czogalla and Herrmann (2011) attempted to introduce the notion of a pedestrian quality attribute and way of evaluating it by physical assessable parameters. For the quality category of comfort, they included two quality elements of level of noise due mainly to vehicle traffic, plus vegetation and shade. They concluded that the high level of noise experienced on footpaths along arterial roads decreased the comfort level and standard of the pedestrian facility.

Huang et al. (2014) defined comfort as 'the hedonic tone of feeling' toward environments. By developing an approach of utilizing people's affective responses to environments, they took account of a person's overall judgment of the environment as reflected in the comfort aspect. They applied the crowdsourcing approach for collecting affective data related to environments and asked participants to rank the level of comfort from uncomfortable ('1') to comfortable ('7'). The results showed their produced AffectRoutes had a significant overlay with the comfortable roads as stated by contributors.

In order to assess overall pleasure in walkability, Appolloni et al. (2019) attributed practicability (as an introduced evaluation category), to the pedestrian's comfort and ease based on current physical conditions of the sidewalks. Three indicators – sidewalk surface, obstacles, and slope were considered to evaluate their effect on walking comfort. They concluded that increasing damage (potholes, chinks, cracks, etc.) in the sidewalk surface, presence of obstacles (from urban furniture to utility equipment and poles) and an increase in the sidewalk slope over than 8% can influence and depreciate the level of pedestrian comfort during walking.

Social comfort is another important aspect of comfort, one which has received less attention in the literature and yet is often presented as one of the decisive elements for recreational walking activity. Pedestrian social comfort normally refers to the number of people present in the street, which causes either social security or social interaction during walking. Social interaction certainly plays an important role in walking quality and grades highly between other walkability factors. Gehl (2011) described the levels of social interaction and the way they happen at various rates in dissimilar setting. For example, pedestrians on their way to a definite destination clearly interact less with one another and their surroundings compared to shoppers, sightseers, or people tarrying in public spaces.

Protecting against extreme environmental factors such as air and noise pollution, heat, wind, humidity, etc are also important in pedestrians' comfort and effect route choice, as pedestrians often seek to decrease their contact to various urban stressors (Dell'Asin, 2010). Pedestrians, generally, exposed to air contamination, which has a damaging effect on people's health and might cause a diverse range of health deterioration (Dratva et al., 2010; Pramendra & Vartika, 2011; Stansfeld et al., 2000). Mölter and Lindley (2015) established a walking network for the Manchester area (UK). Two factors - the lowest particulate matter (PM10) and cumulative nitrogen dioxide (NO2) exposure based on shortest duration, considered as effective factors in pedestrian comfort and were applied in estimating the final routes. Heat stress is another negative environmental factor that also affects pedestrians' comfort, especially in an ageing society and even those younger who have health issues and chronic diseases. With the target of decreasing pedestrians' heat exposure, Rußig and Bruns (2017) developed a pedestrian route planner which was able to find a route with minimal heat stress. They proposed a tool that aids the user to choose the proper daytime with least heat exposure. Noise pollution is strongly connected to road traffic in urban environments (Garg & Maji, 2014; Rey Gozalo et al., 2018) and can affect pedestrians' comfort while city touring. Quieter streets come from the route with less road traffic. With the aim of producing personalized pleasant pedestrian paths based entirely on information from OpenStreetMap, Novack et al. (2018) took into consideration the three street factors of greenness, sociability and quietness. Presented route planner provided users with the choice of selecting routes with minor traffic. In addition, the degree to which users might avoid a route with heavier traffic could be defined by the interactive sidebar.

3.10.6 Discussion

Reviewing the existing literature in PRP studies is an effective way to identify the parameters and aspects used by different authors. It also helps gain a comprehensive insight from the aspects that each researcher considered according to project needs.

By studying and analyzing the relevant thematical literature, we found that apart from a distance as the main factor in route planning, thematic studies have mainly focused on solving routing challenges based on recognized pedestrians' real needs in four key domains of safety, attractiveness, accessibility, and comfort. It is worth mentioning, some studies on analysing pedestrians' behaviours during route finding also acknowledged these factors as influential quality parameters in selecting routes by pedestrians (Alfonzo, 2005; Czogalla & Herrmann, 2011).

Apart from report of identified aspects at each domain, at following, we discussed how PRP parameters in each domain can be structured into hierarchical classifications covering rage of high-level classes to exact spatial variables. Figure 3.2 shows the conceptual framework of proposed hierarchical categories in four domains of safety, accessibility, attractiveness, and comfort.

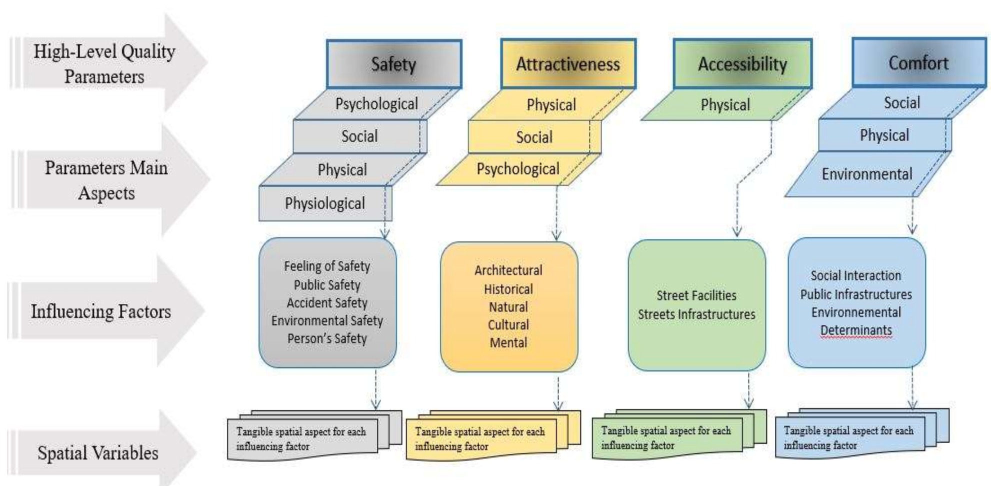


Figure 3.2 Hierarchical taxonomies of quality parameters (SACA) influential in PRP systems

3.10.7 Key Findings: RQ2 - Hierarchical Taxonomy of Safety Parameter Adopted in PRP Systems

As expected, safety is one of the most frequent factors in pedestrian route-planning studies which are strongly influenced by pedestrians' security concerns. The most considered aspects of safety in the relevant literature are public or social safety in the risk of crime, being attacked or disturbed by an offender; pedestrians reassured by considering various safety components at night; low of an accident while crossing the streets; and environmental safety which is the low likelihood of being impacted by natural disasters like flooding, landslide, heatwave, forest fire, etc. Table 3.4 presented hierarchical safety categories covering multiple levels of safety aspects.

Table 3.4 Safety factors influencing pedestrian route selection.

High Level Safety Categories	**Safety Main Aspects**	**Influencing Factors**	**Influencing Factor: Subcategories**	**Spatial Variables**
Psychological Safety	Feelings of Safety	Street Infrastructure	Street Facilities	- Street lights - Traffic lights, signs, and marking. - Sidewalks, - Warning signs at the intersections, - Environment Reflectance and road colours - Intersections sections
			Street Morphological Factors	- Defined boundary on one side of the street - Forest area on one of the sides of the street - Narrow street with presence of blank walls - Turning points
			Urban Landuses	- Narrow alleyway with tall blank walls and long walking distance - Obstacles - Landmark scarcity, - Landmark low visibility
		Urban Infrastructure	Dangerous Area	- Pedestrian low traffic pathways - Too quiet areas

		Traffic Density	Violent Crime		- Murder, rape, aggravated assault, and robbery points
Social Safety	Public Safety	Offending Probability	Property Crime		Larceny, burglary, arson, and motor vehicle theft points
			Other Crimes		- Panhandling, vandalism, drunkenness, obscene language, verbal/physical, drug use/sales, threats, jewellery snatching, pickpocketing points
	Accident Safety	Accident Probability			- Accident with vehicles points - High speed sections - Traffic areas - Crossing violation points
Physical Safety	Environmental Safety	Natural Hazards			- Heatwave, flood, landslide, bushfire, zones.
		Weather phenomena			- Heavy rain, wind, snowfall, fog, ice
Physiological Safety	Person's Safety	Pedestrians Activities	Distracting Activities	**Non/Spatial Factors:**	- Dual task during crossing - Listening to music - Phone conversation - Texting
			Violation Activities		- Negligence and carelessness - Violations of traffic rules
		Subjective Elements	Negative Emotions		- Fear - Anxiety - Discouragement

3.10.8 Key Findings: RQ2 - Hierarchical Taxonomy of Accessibility Parameter adopted in PRP Systems

Unlike a naive understanding that looks at accessibility as just a shorter distance, the term has indeed a broader meaning. We identified different characteristics and subsequently various factors attributing to the accessibility of a path for pedestrians as it relates to street facilities. Those factors that facilitate pedestrian movement, which we label Path Facilitators (PF), and those elements disrupting or hindering the speed and quality of users travelling, called Path Disruptors (PD) here, as presented in Table 4. These spatial factors assume a heavy influence once the model is designed for disabled pedestrians and elderly or pregnant individuals.

Table 3.5 Accessibility factors influencing pedestrian route selection.

High Level Accessibility Categories	**Influencing Factor**	**Spatial Variables**
Physical Accessibility	Street Facilities	- Tactile paving crossing - Pedestrian overpass with accessibility function - Handicap Parking - Handicap Entrance - Roofs and eaves, - Curb cuts, - Braille blocks, - Street Lighting, - Ramp, - Handrail - Street/sidewalk grating - Stairs - Pedestrian overpass - Pedestrian Crossings
	Streets Infrastructures	- Shorter accessible path - Surface structure/conditions - Immovable Obstructions (Elevated manhole covers) - Natural Obstructions (mostly in rural paths like a gully) - Mobile obstacles (Human, bicycle, car traffic) - Sidewalk maintenance - Pavements or sidewalks width - Pavements or sidewalks steepness - Turning radius of ramps

As can be seen from Table 3.5, there are numerous spatial parameters in street infrastructure contributing to improving accessibility or impairing it. These parameters can be extracted from spatial layers, cadastral maps, city master plans, satellite imageries, and surveyed census data.

3.10.9 Key Findings: RQ2 - Hierarchical Taxonomy of Attractiveness Parameter Adopted in PRP Systems

Eye-catching landscape and iconic urban heritage are important scenic parameters that play a significant role in route selection for pedestrians, particularly tourists. These parameters, as summarized in Table 3.6, can be mapped spatially, and updated from Google map dataset.

Table 3.6 Scenic factors influencing pedestrian route selection.

High Level Scenic Categories	Scenic Main Aspects	Influencing Factors	Spatial Variables
Physical Scenic Attractions	Architectural	Urban Architectural	- Iconic buildings - City halls, - Landmarks
	Historical	Urban Historical Heritage	- Museums, - Galleries, - Churches and religious heritage, - Archaeological sites - Monuments
	Natural	Urban Natural Landscape	- Squares, - Parks - Green areas
		Rural Natural Landscape	- Fishing, - Lake, - Riverside, - Jungle, - Ski runs, - Recreational places, - Dike, - Seaside, - Green areas, - Mountains,
Social Scenic Attractions	Cultural	Social Place of Interests	- Restaurants, - Cafes, - Shops
		Social Place of Interactions	- Arterial streets - Street artists, - Street festivals, - Groups of persons, - Temporary exhibitions, - Street markets,

Psychological Scenic Attractions	Mental	Personal Overall Pleasantness	- Street beauty, quietness, and happiness

3.10.10 Key Findings: RQ2 - Hierarchical Taxonomy of Comfort Parameter Adopted in PRP Systems

Parameters addressing comfort can also be categorized into three main classes of social, physical, and environmental. Social comfort is decisive element for recreational walking. Pedestrian social comfort considers the number of people available in the street, a cause either of social security or social interaction during walking. Social interaction ranks highly among other recreational walkability factors. Public infrastructure includes parameters that determine the walkway condition, such elements as traffic-calming measures, and sidewalk factors and facilities. Lastly, environmental determining parameters define the degrees of pleasure in using the route in terms of weather conditions and pleasant environmental factors.

Table 3.7 Comfort factors influencing pedestrian route selection.

High Level Comfort Category	Comfort Main Aspects	Influencing Factors	Spatial Variables
Social Comfort	Social Interaction	Social Events	- Location of People Group Communities - Street markets - Street artists - Street festivals - Temporary exhibitions
		Public Space/Social Places	- Green areas - Parks - Squares - Plazas - Restaurants - Cafes - Shops

Physical Comfort	Public Infrastructure	Traffic Calming Measures	- Road narrowing - Street crossings - Roundabouts - Chicanes - Medians - Lateral shifts - Half and full street closures - Curb extension - Humps - Raised crossings - Intersection radii - Rumble strips
		Sidewalk Factors	- Surface condition - Width - Maintenance - Obstacles - Slope
		Sidewalk Facilities	- Sidewalk's protecting elements - Canopies - Arcades - Water fountains - Sitting facilities - Public toilet - Other street furniture
Environmental Comfort	Environnemental Determinant	Pleasant Environmental factors	- Vegetation - Cast of shadow - Proper temperature - Appropriate humidity - Streetscape
		Extreme Environmental Factors	- Noise - Air pollution - Heat stress

3.11 Limitations of the Study

The objectives of this review are first; to identify high-level route quality parameters and recognised aspects adopted in PRP studies, and second; to find the relationship between reported aspects in each domain and to structure them as hierarchical order categories. Accordingly, the articles are selected from a specific studies of pedestrian route planning. They may dive into a theoretical concept for finding proper route quality parameters according to the surveying questioners or a typical PRP study that has chosen a few criteria for developing PRP models.

The impact of excluding the studies offering only the concepts of pedestrians' walking behaviour or designs of the personalised PRP system is not investigated in this study.

Whether pedestrians as the end-users of PRP systems evaluate the parameters adopted by the articles or not is also not considered. Therefore, the results cannot infer the effectiveness of the parameters and aspects in a real-world scenario. Articles that present the extension of the same project are not excluded, and consequently, the number of papers selected for the review does not uniquely outline a number of PRP studies covering route quality parameters reviewed. Information related to the other heigh-level route quality parameters and aspects were not included in this article. Though a broad search strategy was employed in 10 databases, no articles are distinguished for high-level categories of route quality parameters. However, few articles have been found that introduced new variables as a qualitative parameter in PRP development. Considering these few new variables, which were not matched with our high-level categories, was also beyond this study's scope.

3.12 Summary

In this systematic review, 427 primary studies have become eligible based on a comprehensive search on multiple data sources covering 2000–2021. More than half of the studies considered only the distance parameter, thereby failed to fully incorporate any other route quality parameters. Sufficient details of quality factors affecting pedestrians' route planning are given by 97 studies.

Literature analysis of 97 related articles in pedestrian route planning studies shows:

- %95 of the authors provides unclear definitions of the contributing parameters and their aspects in their proposed route planning systems.
- %85 of the authors provides shallow or unreliable justification for parameters' selection.
- %75 of the authors selects parameters based on either poor literature review, author's experimental mindsets or nearly irrelevant empirical sources.
- %89 of the authors provides undefined insights and goal for required parameters matching with the routing problem.

Overall, our results suggest that the logical/scientific process of selecting relevant parameters in the development of route planning systems is often overlooked in the existing literature. Research analysis supports the theory that mentioned drawbacks are mainly due to lack of systematic reference categorizing pedestrians’ route selection parameters based on multi-level perspectives and different authentic aspects capable to quantify into spatial variables.

Three salient results were derived from this review. First, four domains of safety, accessibility, attractiveness, and comfort recognized as the high-level key quality parameters adopted to any form of pedestrian route planner. Second, different aspects of each quality parameter that have been used in various PRP studies were identified. Vast literature reviews from diverse perspectives led to finding the logical correlation between identified aspects. Parameters' structuring and aspects classifications in hierarchical taxonomies is the last result obtained from this review.

Developed hierarchical categories can bridge the existing gaps in identifying influential factors and relationships between aspects. In addition, they provide researchers considerable insights into pedestrians' route-planning quality parameters and aspects around safety, accessibility, attractiveness, and comfort in PRP systems.

Reviewing the sources and studies in PRP domain led us to conclude that, in selecting the right parameters for designing proper pedestrian routing framework, several essentials should be considered which the most important of them is to determine the purpose of designing route-planner before taking any action, then pick the right variables match with the purpose of proposed route planner.

Though four high-level main quality parameters are considered in planning optimum routes for the pedestrians as shown in Table 2, how to trade-off between their various aspects needs to be further studied, as there is a notable gap in the literature regarding this aspect. The multi-level identified aspects for each quality parameter can be further verified against current PRP needs. It is also important to consider the pedestrians perspective as a major concern. Navigation technology developers need to work closely with the users and the academic experts in the PRP domain to identify end-user requirements related to walking routes quality parameters in complex cities.

Further research on finding associated aspects of safety, accessibility, attractiveness, and comfort as high-level route quality parameters in the PRP domain, along with actual surveying from pedestrians as the end-users, can provide helpful insight for identifying the actual requirements for commuter communities.

CHAPTER 4

PROBLEM DESIGN AND MATHEMATICAL FORMULATION

4.1 Introduction

In urban environments, the efficient and safe movement of pedestrians is fundamental to the overall functionality and liveability of a city. As cities evolve towards smarter and more sustainable forms, the need for advanced pedestrian route planning solutions becomes increasingly critical. Existing route planning systems often lack personalization, overlooking the diverse preferences and priorities of individuals traversing cityscapes. This deficiency is particularly evident when considering factors such as safety, attractiveness, accessibility, and comfort.

Safety concerns are paramount in any urban environment, and pedestrian routes must be designed to minimize the risk of accidents or untoward incidents. Attractiveness is subjective but plays a crucial role in the willingness of pedestrians to utilize specific pathways, impacting overall pedestrian flow and satisfaction. Accessibility is vital for ensuring that routes are inclusive and cater to the needs of individuals with diverse mobility requirements. Finally, the comfort of a route, encompassing aspects like environmental conditions and amenities, significantly influences the overall pedestrian experience.

Despite the undeniable importance of these factors, a comprehensive, multi-objective approach that integrates safety, attractiveness, accessibility, and comfort into a personalized pedestrian route planning framework is notably absent in current research and practical applications. This research seeks to bridge this gap by proposing a novel optimization problem formulation that not only acknowledges the multifaceted nature of pedestrian movement but also leverages cutting-edge evolutionary-based metaheuristic optimization algorithms.

4.2 Novel Personalised Pedestrian Route Planning Conceptualisation

In this section, we delve into the conceptualization of our novel optimization route planning problem tailored for pedestrians. Building upon the insights gained from the literature review we identify the need for a personalized approach that addresses the unique requirements and preferences of pedestrians. This conceptualization serves as the foundational step in defining a comprehensive and innovative problem statement and formulation.

The personalized pedestrian route planning problem revolves around the task of generating optimal walking routes for individuals based on their unique preferences and constraints. Unlike traditional route planning, which often focuses solely on minimizing distance, the innovation of this system is grounded in its capacity on integration of various factors such as accessibility, attractiveness, comfort, and safety. The goal is to craft routes that align with users' individualized requirements, offering an enhanced walking experience tailored to their preferences while considering real-world constraints and objectives.

Four key factors for pedestrian route planning prioritized in this study: safety (path visibility), accessibility (distance), attractiveness (urban land-use types), and comfort (slope percentage of the path).

These factors are carefully selected to create optimal, pedestrian-friendly routes that enhance walkability and livability in urban environments.

By prioritizing these factors, our approach ensures that pedestrians experience safer, more accessible, comfortable, and enjoyable routes. The justification for selecting these parameters is provided in the following sections, demonstrating their alignment with our goal of enhancing pedestrian mobility while maintaining practical and meaningful optimization criteria.

Here is the breakdown and justification for using these influential spatial parameters:

4.2.1 Justification for Selecting Street Visibility Factor for Safety Parameter:

Pedestrian safety is a multifaceted issue influenced by various factors, including road infrastructure, traffic conditions, and urban planning. In this study, we incorporate street lighting as a critical safety parameter due to its direct impact on pedestrian visibility, perception of security, and accident prevention. This decision is based on multiple justifications, including the importance of bright pathways for pedestrian safety and the limitations of data availability for other safety parameters.

1. Importance of Bright Pathways for Pedestrian Safety

Visibility is one of the most crucial factors in pedestrian safety, particularly in low-light conditions and at night. As discussed by Van Bommel (2014), Well-lit streets enhance the ability of pedestrians to:

- **Identify potential hazards** (e.g., uneven pavement, obstacles, or approaching vehicles).
- **Be visible to motorists**, reducing the risk of pedestrian-vehicle collisions.
- **Feel safer**, as well-lit environments deter criminal activities such as theft or harassment.

Studies have shown that poor street lighting is associated with higher accident rates, particularly in urban areas where pedestrian movement is significant (Wanvik, 2009). A study by Steinbach et al. (2015) found that improving street lighting reduces nighttime road collisions by up to 30%. Additionally, brighter pathways are linked to improved community well-being, as people feel more comfortable walking at lower day light, increasing overall pedestrian activity (Ceccato, 2013).

2. Prioritizing Visibility for Safe Walking Conditions

The Street Visibility Parameter in this study is based on the density of streetlights along a given route segment. The rationale behind this parameter is:

- Higher streetlight density indicates better visibility, reducing the likelihood of accidents and increasing pedestrian confidence (Boyce et al., 2000).
- Dark pathways are more dangerous, especially in areas with high traffic or limited pedestrian infrastructure (Renee, 2020).

- Street lighting coverage varies by region, meaning some pedestrian routes may be significantly safer than others due to better illumination (Fotios & Gibbons, 2018).

By integrating the street visibility parameter into pedestrian route optimization, this study ensures that routes with higher visibility are prioritized, thereby minimizing exposure to unsafe, dimly lit paths.

3. Data Collection Limitations for Other Safety Parameters

While multiple factors contribute to pedestrian safety, not all of them can be effectively quantified or consistently measured due to data limitations. Some of the challenges include:

- **Crime Rate Data**:
    - While crime is a major safety concern, comprehensive and real-time crime data at the street level is often not publicly available or lacks granularity (Ceccato & Newton, 2015).
    - Crime rates vary significantly by time and day, making it difficult to use static datasets for route planning (Johnson et al., 2007).
- **Real-time Traffic Data**:
    - While traffic congestion influences pedestrian risk, many open datasets lack detailed pedestrian-vehicle interaction data (Brereton et al., 2007).
    - Traffic patterns change dynamically, making it challenging to incorporate static traffic risk assessments (Wang et al., 2011).
- **Surveillance and Emergency Response Infrastructure**:
    - The presence of CCTV cameras or emergency call stations may increase perceived safety, but such data is not consistently mapped or available in public geospatial datasets (Byrne & Pease, 2012).

Due to these limitations, street lighting data offers a more accessible, standardized, and quantifiable measure of pedestrian safety. Unlike crime and traffic data, streetlight locations are typically available in urban planning datasets, allowing for accurate integration into geospatial analysis.

4.2.2 Justification for Selecting Urban Land-Use Factor for Attractiveness Parameter:

For the sake of finding route attractions, we focus on urban land-use types to enrich (Forsyth & Krizek, 2010)pedestrians' walking experiences. Pedestrians often seek routes that pass-through areas with diverse urban features such as parks, shopping districts, cultural hubs, and residential neighbourhoods, etc (Ewing & Handy, 2009). Considering the following reasons we selected urban land-use types as a significant parameter for our study.

1. **Enhancing Walking Experience**
   Pedestrians prefer routes that pass through vibrant urban spaces such as parks, commercial areas, and cultural hubs, which provide aesthetic, social, and recreational benefits (Mehta, 2013). Green spaces improve well-being, while commercial zones and cultural districts create lively and interactive environments, making walking more enjoyable (Hall & Ram, 2018).
2. **Behavioral and Psychological Factors**
   Studies indicate that pedestrians are more likely to choose routes that offer visual stimulation, safety, and social interactions over the shortest path (Sarraf & McGuire, 2020). Active street life and mixed land-use areas encourage higher pedestrian movement and engagement.
3. **Practical and Data-Driven Approach**
   Urban land-use data is widely available and provides an objective metric for attractiveness. Unlike subjective factors, land-use information can be consistently integrated into GIS-based pedestrian routing models to enhance route selection based on diverse environmental features (Basu et al., 2022).

By incorporating urban land-use types, the pedestrian route planning system prioritizes routes that are not only efficient but also engaging and enjoyable.

4.2.3 Justification for Selecting Path Distance Factor for Accessibility:

Accessibility in pedestrian route planning is largely influenced by path distance, as shorter routes reduce travel effort and make walking a more viable option for all users (Conticelli et al., 2018). Research indicates that pedestrians generally prefer direct and efficient paths to their destinations, especially in urban environments where time and convenience are key factors (MOLLAZADEH, 2016).

Path distance is a fundamental factor in pedestrian route planning, directly influencing walkability and accessibility. We selected this parameter for the following reasons:

1. **Minimizing Travel Effort** – Shorter routes reduce physical exertion, making walking more practical for a wider range of users, including the elderly and people with mobility impairments (Forsyth & Krizek, 2010).
2. **Improving Route Efficiency** – Research shows that pedestrians prefer direct paths that minimize unnecessary detours, as longer routes discourage walking and reduce overall mobility (MOLLAZADEH, 2016).
3. **Balancing Accessibility with Other Factors** – While pedestrian experience involves multiple aspects (e.g., safety and attractiveness), distance remains a core determinant of route selection. Optimizing for shorter paths ensures efficiency while maintaining trade-offs with other key criteria (Tong & Bode, 2022).

By incorporating path distance into our multi-objective optimization model, we ensure that our approach aligns with real-world pedestrian preferences while maintaining accessibility and practicality.

4.2.4 Justification for Selecting Slope Percentage of the Path for Comfort:

In addition to safety, accessibility, and attractiveness, this study introduces a new criterion for comfort based on the slope percentage of the path. Pedestrians typically prefer routes with gentle slopes or flat terrain, as steep inclines can be physically challenging and uncomfortable, particularly for individuals with mobility limitations. By incorporating the path slope percentage, we aim to offer pedestrian-friendly routes that minimize physical exertion and enhance overall comfort during walking journeys.

We selected the slope percentage as a key factor for comfort in pedestrian route planning for the following reasons:

1. **Impact on Walking Ease** – Steep slopes increase the physical effort required to walk, particularly for vulnerable groups such as the elderly or people with

mobility impairments. Gentle slopes or flat paths provide a more comfortable and accessible experience (C. Wang et al., 2020).

2. **Energy Consumption and Fatigue** – Research shows that walking on steeper gradients can lead to increased fatigue and reduced walking speeds, discouraging pedestrians from using certain routes (Cheng, 2014).
3. **Public Health and Well-being** – Routes with gentle slopes encourage walking by reducing strain, thereby promoting physical activity and improving overall health, especially in urban environments where pedestrian movement is crucial for sustainable mobility (Baobeid et al., 2021).

By including slope percentage in our study, we prioritize pedestrian comfort, ensuring the selection of routes that cater to the needs of a broader population while maintaining accessibility and walkability.

4.3 Basic Terminologies

Before formulating the problem and objective functions the following terminologies are provided and defined first for further clarities.

I. **Route Planning:** The route planning is defined as searching an optimal path *p* between the source and destination nodes in a graph G (V, E) (Dijkstra, 1959) considering four optimization objectives.

II. **Graph Definition:** In order to model this problem, we represent the urban pedestrian network as a Graph. In mathematics, and more specifically in graph theory, a graph G (V, E) is a composition amounting to a set of features in which some sets of the objects are in some sense "related". In discrete mathematics, Graphs are one of the study objects (West, 1996). Where:

- **Edges (E):** These represent the paths between vertices, with attributes such as length, slope percentage, and path type (e.g., pedestrian walkway, sidewalk, or road type), etc.

  $E = [e_1, e_2, \ldots, e_m] \in E$ is a set of edges of graph G denoting road segments connecting two vertexes in V (*m* is the number of edges).

- **Vertices (V):** Each vertex symbolizes an intersection, an urban land-use type, or a significant juncture in the pedestrian network.

$V = [v_1, v_2, \ldots, v_n] \in V$ is a set of vertexes of graph G denoting road intersections (n is the number of vertexes), and

III. **Segment Definition**: a segment in a graph G (V, E) of is a combination of some vertexes which connected physically (Figure 4.1).

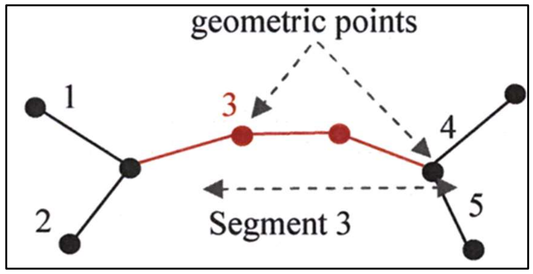


Figure 4.1 Segments in a graph (Cherfaoui et al.)

IV. **Path Definition:** A path p is a sequence of segments from the source node v_s to the destination node v_d, (Figure 4.2 and Equation 4.1).

$$Optimal\ Path = [s_1 * v_{1,} s_2 * v_{2,} \ldots s_j * v_{i,}]\ where\ 1 < i < n\ \&\ s_i \in [0, 1] \qquad (4.1)$$

Where s_i is a Boolean variable (0 or 1) that is used to determine if the vertexes v_i is chosen in the suggested pass ($s_i = 1$) or it is not included in the optimal path ($s_i = 0$).

For example, in the image below, the green path = $[0 * v_1, 1 * v_2, 1 * v_3, 0 * v_4, 1 * v_5]$

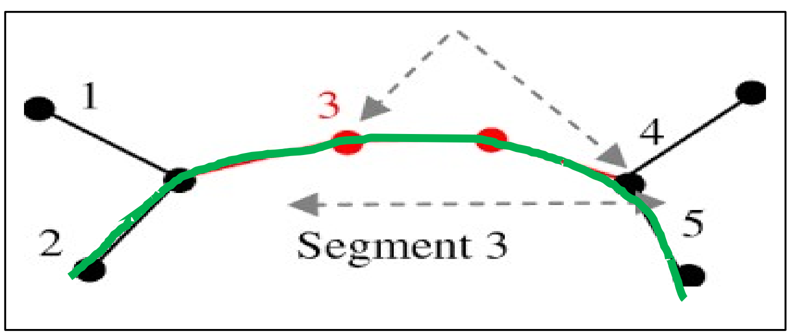


Figure 4.2 Example of calculated path over the graph.

V. **Elevation Definition:** The elevation (Z) of a geographic location is its height above or below a fixed reference point, most commonly a reference geoid, a mathematical model of the Earth's sea level as an equipotential gravitational surface (USGS, 2017).

VI. Geographic Coordinate: Coordinates are pairs (X, Y) in a two-dimensional space referenced to a horizontal datum. Whereas triplets (X, Y, Z) of points not only have position, but also has height referenced to a vertical datum. In other words, the X- and Y-values represent horizontal position. Whereas the Z-value represents the vertical position (GIS Geography 2020).

4.4 Mathematical Formulation of Multi-Objective Optimization Problem

In this section, we delve into the mathematical formulation and modelling approach used in the proposed "Multi-Objectives Personalized Pedestrian Path Routing" problem.

The mathematical formulation for the multi-objective pedestrian route planning problem, covering all four the objectives seek routes that balance accessibility, attractiveness, comfort, and safety, offering a set of solutions that represent trade-offs between these conflicting objectives.

The optimization algorithm will aim to find solutions that are not dominated by any other solution in terms of these objectives, providing a range of choices for personalized pedestrian route planning. This formulation incorporates all the constraints logically and concisely.

In addition, we are emphasizing the optimization process including the use of **Pareto-Based Multi-Objectives Ant Colony Optimization (PB-MOACO) Algorithm**, leading Pareto Front Solutions, and most importantly, a post-optimization user preference. As mentioned this approach captures the essence of a **Pareto-based approach** with personalization integrated at the final decision stage.

To formulate the pedestrian route planning as a multi-objective optimization problem, we need to define the problem in terms of **decision variables, objectives and objective functions, and constraints (explained in problem formulation).**

4.4.1 Decision Variables:

The decision variables are the edges selected in the network graph to construct the path (P).

$x_{ij} = 1$ if the edge is included in the route.

$x_{ij} = 0$ if the edge is not used.

- **A path (P)** is a sequence of connected edges (i,j) in the network that forms a continuous route from the origin to the destination.

4.4.2 Objectives:

The problem has four primary objectives to optimize, each representing a key factor for pedestrian-friendly routes:

- **Maximize Accessibility** $\left(\boldsymbol{f}_{\text{Accessibility}}\ (\boldsymbol{P})\right)$: • Maximize the total reverse distance for the selected path.
- **Maximize Attractiveness** $\left(\boldsymbol{f}_{\text{Attractiveness}}\ (\boldsymbol{P})\right)$: Enhancing the route based on urban and natural features and landmarks.
- **Maximize Safety** $\left(\boldsymbol{f}_{\text{Safety}}\ (\boldsymbol{P})\right)$: Prioritizing segments with better visibility and lighting.
- **Maximize Comfort** $\left(\boldsymbol{f}_{\text{Comfort}}\ (\boldsymbol{P})\right)$: Selecting paths that provide a comfortable walking experience based on slope.

4.4.3 Objective Functions:

4.4.3.1 Accessibility Objective Function

This objective function formula for accessibility based on Euclidean Distance (Danielsson, 1980), including the distance formula and a constraint to ensure that distances are minimized. The objective is to maximize the overall accessibility, where accessibility is determined by the inverse of the distance for the path. To bring values into a more readable range, we also multiply the inverse distance value to a scaling factor k=10^6. Finally, the constraint ensures that the distance for between the source and the destination node certain maximum value (Equations 4.2 to 4.5).

Accessibility Objective Function Formula:

$$f_{\text{accessibility}}(P) = \frac{1}{\sum_{(i,j)\in P}\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}} \tag{4.2}$$

Where: $f_{\text{accessibility}}(P)$ represents the Accessibility objective function.

Subject to:

1. **Maximum Distance Constraint**:

$$\sum_{(i,j)\in P} \text{Distance } (i,j) \le D_{\max} \tag{4.3}$$

Where:

- Distance(i,j): Euclidean distance between the start and end points of segment (i,j), calculated as:

$$\text{Distance } (i,j) = \sqrt{(x_{End} - x_{Start})^2 + (y_{End} - y_{Start})^2} \tag{4.4}$$

where:

- (x_{Start}, y_{Start}) : Coordinates of the start point of the segment.
- (x_{End}, y_{End}) : Coordinates of the end point of the segment.

2. **Inverse Distance Function**

$$InverseDistance(P) = \left|\frac{1}{\sum_{(i,j)\in P} \text{Distance } (i,j)}\right| * \ k \tag{4.5}$$

where:

- P : Sequence of connected edges (i,j) in the network that forms a continuous Path (P) from the origin to the destination.
- *Euclidean Distance(si)* is the straight-line distance between the start and end points of the segment.
- *InverseDistance(si)* is a function that quantifies the inverse of distance, representing higher accessibility for shorter distances.
- $D_{\max}$ is the maximum allowable distance for a path (P).
- K is a Scaling Factor equal to 10^6 multiplied to inverse distance to avoid very small values and keep values in a reasonable range.

Key Points:

1. The Euclidean distance formula is applied to each segment (i, j) of the path (P) to compute Distance (i, j).
2. The total distance $\sum_{(i,j)\in P}$ Distance (i, j) is the sum of distances for all segments in the path (P).
3. Maximizing the inverse distance effectively minimizes the total path distance, which aligns with better accessibility. This is because shorter distances yield higher values for the inverse distance function.

4.4.3.2 Attractiveness Objective Function

The Attractiveness Objective Function aims to optimize pedestrian routes by prioritizing routes with higher aesthetic and experiential value. This function evaluates paths based on the presence and types of attractions, such as urban amenities, natural landscapes, and landmarks, which contribute to a pleasant walking experience. By considering these factors, the function encourages the selection of routes that provide not just functionality but also enjoyment, aligning with pedestrian preferences for scenic and engaging environments.

The attractiveness of a path is determined by evaluating specific attributes of the network's nodes, which are linked to Urban Landuse types. Each node is assigned a score based on the type and quality of the attraction it represents. These scores are then aggregated across all nodes in the path to calculate the overall attractiveness of the route (Equation 4.6).

Attractiveness Objective Function Formula:

$$f_{\text{Attractiveness}}(P) = \sum_{v\in P} \text{AttractivenessScore}(v) \qquad (4.6)$$

Subject to:

1. P represent a sequence of connected edges (i,j) in the network that forms a continuous Path (P) from the origin to the destination.

Where:

- $f_{Attractiveness}\ (P)$: Total attractiveness score of the path (P).
- $v \in P$: Set of nodes representing the path (P).

2. AttractivenessScore (v) : Score assigned to node v based on its type of attraction and is determined by the presence and type of attraction at node v.

Where:

Each node v in the network is assigned an attractiveness score based on the type of Urban Landuse (UL) associated with it. These scores are defined as follows:

$$\text{AttractivenessScore } (v) = \begin{cases} 10, & \text{if UL is 'National park'} \\ 9, & \text{if UL is 'Recreation and culture'} \\ 8, & \text{if UL is 'Coastal waters'} \\ 7, & \text{if UL is 'Commercial services'} \\ 6, & \text{if UL is 'Urban residential'} \\ 5, & \text{if UL is 'Public services'} \\ 4, & \text{if UL is 'Other conserved area'} \\ 3, & \text{if UL is 'Land in transition'} \\ 2, & \text{if UL is 'Manufacturing and industrial'} \\ 1, & \text{if UL is 'Highways'} \\ -3, & \text{if UL is 'Railways'} \end{cases}$$

Key Points:

- Node-Specific Scoring: Each node is evaluated based on the POI type it represents. Higher scores are assigned to nodes with features that enhance attractiveness, such as parks or cultural sites, while lower or negative scores are assigned to less desirable features like highways or railways.
- Path Aggregation: The attractiveness scores of all nodes along a path are summed to calculate the total attractiveness of the route.
- Optimization Goal: The objective is to maximize $f_{Attractiveness}(P)$, favoring paths with higher cumulative attractiveness scores.

4.4.3.3 Safety Objective Function

The Safety Objective Function focuses on optimizing pedestrian route planning by prioritizing segments with better visibility, as measured by the presence of streetlights. Visibility is an essential safety factor, especially for pedestrians traveling during low-light conditions. By considering the density of streetlights along each segment, the function quantifies safety into a score that can guide the selection of the safest route.

Each segment in the network is assigned a Safety Ratio (ST), calculated as the number of streetlights divided by the length of the segment (Equation 4.8). This ratio reflects the intensity of lighting per unit length. Based on predefined thresholds, the Safety Ratio is categorized into different safety levels, with corresponding Safety Scores assigned to each category.

The objective function aggregates the safety scores of all segments in a given path to derive the total safety score, as each segment of the path needs to be bright (equation 4.7).

The scoring system is tailored to reward segments with Medium Safety (ST < 0.02) to Excellent Safety (ST ≥ 1.21) which are the safer for pedestrians, while penalizing segments with less streetlights as they approach the maximum allowable ST threshold (ST < 0.01). Justification about safety threshold discussed at Section 4.2.1.

Safety Objective Function Formula

$$f_{\text{Safety}}(P) = \sum_{(i,j)\in P} \text{SafetyScore}(i,j) \qquad (4.7)$$

Subject to:

1. P represent a sequence of connected edges (i,j) in the network that forms a continuous Path (P) from the origin to the destination.
2. SafetyScore(P) is determined based on the **Safety Ratio** of each edge *segment*.
3. Additional constraints for path validity (e.g., avoiding unsafe or restricted areas) may apply.

Where:

- $f_{\text{Safety}}(P)$: Total safety score of the path P.
- SafetyScore (i,j) : Score assigned to segment (i, j) based on its Safety Ratio.

- SafetyRatio(i, j): Calculated as:

$$\text{SafetyRatio}(\,i,j) = \frac{\text{Number of Streetlights}}{\text{Length of Segment (meters)}} \tag{4.8}$$

Scoring Strategy:

Each segment is assigned a Safety Score based on its Safety Ratio, according to the following classifications:

$$\text{SafetyScore}\ (i,j) = \begin{cases} -3, & \text{if } 0 \leq \text{SafetyRatio}(\,i,j\,) < 0.01(\text{ Poor Safety }) \\ 5, & \text{if } 0.01 \leq \text{SafetyRatio}(\,i,j) \leq 0.02(\text{ Medium Safety }) \\ 10, & \text{if } 0.02 < \text{SafetyRatio}(i,j) \leq 0.04(\text{ Good Safety }) \\ 15, & \text{if } 0.04 < \text{SafetyRatio}(i,j) \leq 1.21(\text{ Excellent Safety }) \end{cases}$$

Key Points:

- **Safety Ratio Calculation**: Each segment is evaluated based on its Safety Ratio, a measure of the density of streetlights relative to the segment length.
- **Safety Score Assignment**: The Safety Ratio is classified into categories ranging from "Poor Safety" to "Excellent Safety." The Safety Score reflects this classification and increases as the lighting conditions improve.
- **Path Aggregation**: The safety scores for all edges in a path are summed to determine the total safety score of the route.
- **Optimization Goal**: The objective is to maximize $f_{Safety}(p)$, encouraging paths with higher cumulative safety scores.

4.4.3.4 Comfort Objective Function

The Comfort Objective Function is designed to prioritize pedestrian routes based on the slope of the terrain. Slope plays a critical role in pedestrian comfort, as steeper paths are more physically demanding and less accessible for individuals such as the elderly, people with disabilities, or those carrying heavy loads. By incorporating slope into the route planning process, the comfort objective ensures that selected paths are as convenient and accessible as possible for users.

This function assigns a comfort score to each segment of a path based on its mean slope percentage (Equation 4.9). The scoring system is tailored to reward segments with gentle slopes (0–3%), which are the most comfortable for pedestrians, while penalizing steeper segments as they approach the maximum allowable slope threshold (15% to 30%) as discussed at Section 4.2.4. The comfort scores are cumulative for all segments of a path, and the goal is to maximize this total score, thus favoring routes with lower slopes (Equation 4.10).

Comfort Objective Function Formula:

The total comfort score for a path is the sum of the comfort scores of all its segments:

$$f_{\text{Comfort}}(P) = \sum_{(i,j)\in P} \text{ComfortScore}\ (i,j) \qquad (4.9)$$

Subject to:

1. **Maximum Slope Constraint:** The function includes constraints to ensure practicality:

$$\max_{(i,j)\in P} \text{Slope}\ (i,j) \leq S_{max} \qquad (4.10)$$

- Paths cannot include slopes exceeding the maximum allowable slope of 30%.
- Only valid and connected paths in the graph representation are considered.

Where:

- **Scoring Strategy:** The comfort score (i,j) assigned to each segment based on its mean slope percentage:

$$\text{ComfortScore}\ (i,j) = \begin{cases} 15, & \text{if } 0 \leq \text{Slope}(i,j) < 3 \\ 10, & \text{if } 3 \leq \text{Slope}(i,j) < 5 \\ 8, & \text{if } 5 \leq \text{Slope}(i,j) < 8 \\ 5, & \text{if } 8 \leq \text{Slope}(i,j) < 30 \\ -5, & \text{if } 15 \leq \text{Slope}(i,j) \leq 30 \end{cases}$$

- **Slope $(\boldsymbol{i},\boldsymbol{j})$:** Mean slope percentage of the segment (i,j), calculated as show in Equation 4.11:

$$\text{Slope}\ (i,j) = \left| \frac{\text{Height}_{\text{End}} - \text{Height}_{\text{Start}}}{\sqrt{(X_{\text{End}} - X_{\text{Start}})^2 + (Y_{\text{End}} - Y_{\text{Start}})^2}} \right| \times 100 \qquad (4.11)$$

where:

- Height Start and Height End: Elevation values at the start and end points of the segment.
- X_{Start} , Y_{Start} : Coordinates of the start point.

- $X_{\text{End}}, Y_{\text{End}}$: Coordinates of the end point.

- ***P***: Represents the path as a sequence of nodes and edges in the graph.
- **30%:** Maximum allowable slope percentage for the planned path.

This formula accounts for the Euclidean distance between points and ensures that both steep uphill and downhill slopes are penalized equally.

Key Points:

By optimizing for comfort, the resulting paths will:

- Have the Minimum steep slopes wherever possible.
- Favor routes with gentle terrain, enhancing accessibility and reducing physical strain for users. This approach balances practicality with user comfort, making it particularly useful for urban pedestrian route planning.

4.4.4 Multi-Objective Optimization Problem

The problem is to find the optimal pedestrian path P in a network G (V, E) where V is the set of nodes and E is the set of edges, such that the following four objectives are treated independently (Equation 4.12):

$$\text{Maximize Accessibility (Path Distance)}: f_{\text{Accessibility}}\ (P) = \frac{1}{\sum_{(i,j)\in P}\ Distance_{ij}},$$
$$\text{Maximize Attractiveness (Urban Land-Use Types)}: f_{\text{Attractiveness}}(P) = \sum_{(i,j)\in P} \text{AttractivenessScore}(i,j),$$
$$\text{Maximize Safety (Street Visibility)}: f_{\text{Sfety}}(P) = \sum_{(i,j)\in P} \text{SafetyScore}(i,j),$$
$$\text{Maximize Comfort (Slope Percentage)}: f_{Comfort}(P) = \sum_{(i,j)\in P} \text{ComfortScore}(i,j)$$

(4.12)

Subject to:

$\text{P} \in \text{P}, \text{P} = \{\text{P} \mid \text{P connects origin to destination in the network}\}$ (Connectivity (Path Validity))

$\sum_{(i,j)\in P}$ Distance $(i,j) \leq D_{\max}$ (Maximum Path Distance)

Slope $(i,j) \leq S_{\max}, \forall (i,j) \in P$ (Maximum Slope Percentage)

SafetyRatio $_{(i,j)} \geq \text{r}_{min},\ \forall_{(i,j)} \in \text{P}$ (Safety Threshold)

$UL_v \neq \emptyset, \ \forall_v \in \mathrm{P}$ (Valid Landuse Attribute)

$(i, j) \in \mathrm{P} \Longrightarrow$ e is a valid edge in the pedestrian network graph. (Network Constraints)

$f_{\text{Accessibility}}(P), f_{\text{Attractiveness}}(P), f_{\text{Safety}}(P), f_{\text{Comfort}}(P) \geq 0$ (Non-Negativity of Scores)

Where:

- $f_{\text{Accessibility}}(P)$: Accessibility Objective Function based on street visibility.
- $f_{\text{Attractiveness}}(P)$: Attractiveness Objective Function based on urban land-use types.
- f_{Safety} (P) : Safety Objective Function based on path distance.
- f_{Comfort} (P) : Comfort Objective Function based on slope percentage.
- P : Represent a sequence of connected edges (i,j) in the network that forms a continuous Path (P) from the origin to the destination.
- O : Origin node in the graph.
- D : Destination node in the graph.
- D_{max} : Maximum allowable path distance.
- S_{max} : Maximum allowable slope percentage.
- Safety Threshold: Each edge in the path must have a Safety Ratio above a minimum threshold (r_min) for safety-critical scenarios.
- Valid Urban Landuse: Each node $v \in$ P must have valid attributes for attractiveness calculation.

4.4.5 Implementation Steps (Covering all Four Objectives)

High-level processing steps designed based on proposed methodology framework.

[Start]
Input:
- Graph G (V, E) with nodes V and edges E
- Objective functions:
  * Accessibility: f_Accessibility(x) = 1 / (∑_(i,j)∈P Distance_ij)
  * Attractiveness: f_Attractiveness(x) = ∑_(i,j)∈P AttractivenessScore(i,j)
  * Safety: f_Safety(x) = ∑_(i,j)∈P SafetyScore(i,j)
  * Comfort: f_Comfort(x) = ∑_(i,j)∈P ComfortScore(i,j)
- Number of ants (m)
- Number of iterations (T)
- Pheromone matrix τ(e) for each edge e ∈ E
- Heuristic matrix η(e) based on individual objective heuristics
- Evaporation rate ρ
- Archive PF (Pareto front, initially empty)
- α, β: influence of pheromone and heuristic information

Initialize:
- Set pheromone levels $\tau(e) = \tau_0$ ∀ e ∈ E
- Compute heuristic information η(e) based on problem-specific rules

- Set iteration counter $t = 0$

While t < T do:

- Initialize an empty temporary solution set TEMP_PF
- For each ant $k \in [1, ..., m]$ do:
    - Select a random start node v_start and destination v_goal
    - Construct path P_k using the transition probability:
      $p\_ij = (\tau\_ij^\alpha * \eta\_ij^\beta) / \sum (\tau\_il^\alpha * \eta\_il^\beta) \; \forall \, l \in$ Neighbors(i)
    - Store the path P_k

    - Evaluate path P_k for all objectives:
      F(P_k) = [f_Accessibility(P_k), f_Attractiveness(P_k), f_Safety(P_k), f_Comfort(P_k)]

    - Add P_k to TEMP_PF if it is non-dominated
- Pareto Front Update:
    - Merge TEMP_PF with current Pareto front PF
    - Remove dominated solutions from PF to maintain only non-dominated solutions

- Pheromone Update:
    - Evaporate pheromone: $\tau(e) \leftarrow (1 - \rho) * \tau(e) \; \forall \, e \in E$
    - Reinforce pheromones along non-dominated paths in PF:
      $\tau(e) \leftarrow \tau(e) + \sum (\Delta\tau\_k(e))$ for each P_k ∈ PF
      where $\Delta\tau\_k(e) = Q / f(P\_k)$, Q is a constant
- $t \leftarrow t + 1$

[End While]

Post-Optimization: User Preference-Based Selection

- Normalize objective values in Pareto Front PF

- Apply user-defined weights [w_Accessibility, w_Attractiveness, w_Safety, w_Comfort]

- Compute weighted score for each solution in PF:

  S(P_k) = w_Accessibility * f_Accessibility(P_k)

  + w_Attractiveness * f_Attractiveness(P_k)

  + w_Safety * f_Safety(P_k)

  + w_Comfort * f_Comfort(P_k)

- Select the best path P_final based on the highest S(P_k)

Output:

- Pareto-optimal set of paths PF

- Final selected path P_final based on user preferences

[END]

4.5 Chapter Summary

This chapter outlines a comprehensive framework for developing personalized pedestrian route planning strategies in urban settings. Chapter 4 lays out a detailed mathematical and conceptual foundation for a multi-objective pedestrian route planning system that goes beyond conventional distance minimization to create safer, more attractive, accessible, and comfortable urban pathways. It provides a conceptual and methodological basis for developing systems that deliver safe, attractive, accessible, and comfortable urban walking experiences, thereby addressing the multifaceted needs of modern urban mobility.

Key Themes and Concepts:

- **Multi-Dimensional Priorities:**
  The chapter emphasizes that pedestrian routes should not only be short but also safe, visually appealing, accessible to people with various mobility needs, and comfortable in terms of terrain. Each of these aspects is treated as a core objective in the planning process.

- **Safety Through Enhanced Visibility:**
  Safety is primarily measured by evaluating the availability of street lighting. Well-lit routes are associated with reduced risk of accidents and a heightened sense of security. Due to the challenges in obtaining real-time crime or traffic data, street illumination is used as a practical and quantifiable proxy for safety.

- **Enhancing Route Attractiveness:**
  The attractiveness of a route is determined by the urban environment it traverses. By incorporating diverse urban land-use features—such as parks, cultural sites, and commercial areas—the system aims to create walking paths that are both engaging and enjoyable, enhancing the overall pedestrian experience.

- **Optimizing Accessibility:**
  Accessibility is viewed in terms of route efficiency and ease of travel. Shorter and more direct paths are preferred, as they require less physical effort, thereby accommodating a broader range of users, including those with mobility constraints.

- **Prioritizing Comfort:**

  Comfort is largely influenced by the physical characteristics of the route, particularly the steepness of the terrain. The framework favors routes with gentle slopes, thereby reducing physical exertion and fatigue for pedestrians.

- **Graph-Based Modeling:**

  The urban pedestrian network is conceptualized as a graph where intersections and notable urban features serve as nodes, and the connecting pathways as edges. This abstract representation allows the formulation of the route planning problem as one of finding optimal paths within this network.

Integrated Optimization Approach:

The chapter introduces an optimization strategy based on evolutionary and Pareto-based techniques. This method generates a spectrum of viable solutions that balance the often conflicting objectives. Ultimately, the framework offers personalized options by incorporating post-optimization adjustments based on individual preferences.

CHAPTER 5

SYSTEM DESIGN & ARCHITECTURE

5.1 Introduction

This chapter presents the detailed design of the multi-objective personalized pedestrian route planning system, which integrates multiple components to deliver final optimized walking paths based on individual preferences and environmental considerations. The system design is structured around a combination of data acquisition, processing, advanced algorithmic solutions, Graph-Based Representation Module, PB-MOACO Optimization Engine and Post Optimization. In addition, we discuss details of our employed methodology for performance evaluation.

5.2 System Architecture Overview

The system design for personalized pedestrian route planning comprises a synergistic integration of various components, each playing a crucial role in generating optimal walking path tailored to individual preferences and requirements. At its core, the system leverages GIS tools and techniques to seamlessly process spatial data. Data processing outputs feed into a multi-dimensional graph model in Python, which serves as the main feed for the advanced algorithmic solution. The routes generated by the algorithm are further refined through a post-optimization stage that incorporates user preferences, ultimately yielding a final, optimized pedestrian route that caters to the diverse needs of urban pedestrians. A visual representation of the system architecture is provided in Figure 5.1, with subsequent paragraphs discussing each component briefly.

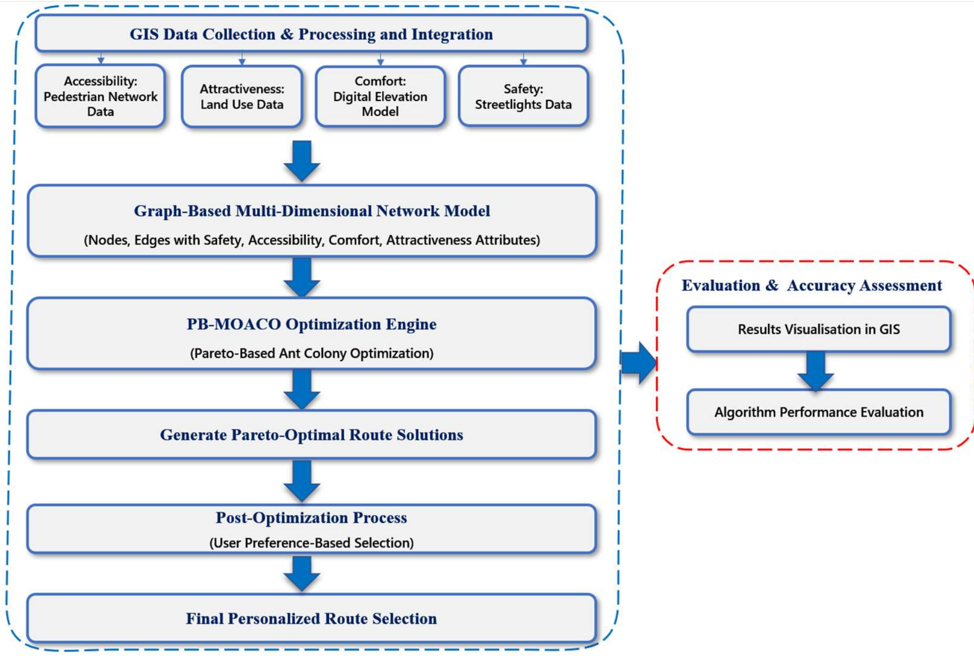


Figure 5.1 Diagram of System Overview

Data Collection, Processing and Integration: Central to the system design as the first essential component is acquisition, processing and the integration of diverse datasets essential for pedestrian route planning. These datasets include pedestrian network data, land use data, streetlight data, and digital elevation model data in GIS format. Each dataset undergoes meticulous preprocessing and processing steps to ensure compatibility and consistency. Leveraging Python scripting and ArcGIS Pro, we harmonize these datasets to create a comprehensive spatial database that forms the basis for route generation. Details on this process are provided in section 5.3.

Graph-Based Multi-Dimensional Network Module: The system utilizes a Multi-Dimensional Graph Model, which represents the urban pedestrian network, capturing attributes such as safety, accessibility, comfort, and attractiveness. It means that the integrated datasets are then transformed into a multi-dimensional graph data structure model, where nodes represent key points in the pedestrian network, and edges denote the connections between them. This graph model captures various attributes such as segment length, slope, number of streetlights, and landuse types that are used in measuring objective functions including: safety, accessibility, comfort, and attractiveness, which are essential considerations in route planning. By encapsulating these attributes within the graph structure, we create a weighted graph where edges store multi-objective attributes. It is a holistic representation of the urban environment, enabling efficient pathfinding algorithms to navigate the pedestrian network. Further explanation is available in section 5.4 and 5.4.1.

Algorithmic Solution & Structure: A key optimization technique employed in the system is Pareto-Based variant of Multi-Objective Ant Colony Optimization (PB-MOACO), a metaheuristic algorithm inspired by the foraging behaviour of ants. PB-MOACO is utilized to search for optimal routes within the multi-dimensional graph model, leveraging pheromone trails and heuristic information to guide the exploration process. By iteratively refining route solutions based on feedback from previous iterations, PB-MOACO effectively balances exploration and exploitation, yielding routes that are optimized for various objectives. More details provided at section 5.5.1 for designing PB-MOACO algorithmic function, and section 5.5.2 for Pareto optimal set details.

For more information on why we selected this approach over other multi-objectives algorithms, please refer to Chapter 2, section 2.8.2.1.

Post Optimisation: The post-optimization function is another major component of our algorithmic system design, it is applied to the Pareto-optimal set of solutions to provide a final, user-preference-based selection. Once the PB-MOACO has produced pareto optimal solutions, the post-optimization function further refines these, and select one of the pareto optimal solutions by considering user preferences, which are incorporated as weightings for the key parameters, such as safety, accessibility, comfort, and attractiveness. This ensures that the final route selection is tailored to the individual pedestrian's specific needs and priorities. This process is explained in section 5.5.3.

Performance Evaluation: To ensure the reliability and effectiveness of the system, a comprehensive performance evaluation framework is implemented. This includes validation exercises, comparative analyses, and real-world testing scenarios to assess the quality of generated routes, evaluate algorithmic performance, and validate the system's ability to meet user-defined criteria.

For benchmarking purposes, we compare the final solution derived from our proposed Pareto-Based Approach with the solutions generated by two established algorithms, Dijkstra and MOACO-WA (An overview on Multi-Objective Ant Colony Optimization via Weighted Aggregation (MOACO-WA) along with details of Optimisation Process discussed at section 5.6.1).

These algorithms serve as benchmarks to evaluate the performance of our approach, providing a basis for comparison with their respective single solution outcomes. Further details about Rationale behind algorithm selection in performance evaluation brought at section 5.7.

5.3 Data Collection, Processing and Integration

The first part of the methodology provides an in-depth exploration of the mechanisms involved in gathering and preparing various datasets crucial for personalized pedestrian route planning. This section encompasses four key components: Pedestrian Network Data Acquisition and Processing, Land Use Data Acquisition and Processing, Streetlight Data Acquisition and Processing, and Digital Elevation Model Acquisition and Processing.

Section 5.3.1 delves into the methodologies employed to obtain and process pedestrian network data using Python and ArcGIS Pro. It outlines the procedures for acquiring datasets related to pedestrian pathways, sidewalks, crossings, and other pertinent features. Additionally, it details the steps involved in processing this data, including data cleaning, integration, and conversion into a format suitable for graph-based analysis.

The focus of section 5.3.2 shifts to the acquisition and processing of land use data within a ArcGIS Pro environment. It elucidates the techniques utilized to procure datasets containing information about landuse types such as parks, commercial areas, and cultural landmarks. The sub-section also discusses the processing steps necessary to extract relevant attributes from the land use data and integrate them into the pedestrian route planning framework.

Section 5.3.3 explores the procedures involved in acquiring and processing streetlight data using ArcGIS Pro. It delineates the methods for obtaining datasets containing information about streetlight locations and illumination levels. Moreover, it outlines the steps for processing this data to derive insights relevant to pedestrian safety based on visibility along pathways.

Finally, section 5.3.4 examines the acquisition and processing of digital elevation model (DEM) data within a GIS context. It elucidates the techniques for obtaining datasets containing information about the topography and slope of the terrain.

Furthermore, it discusses the processing steps required to incorporate DEM data into the pedestrian route planning system, enabling considerations of path gradient and elevation changes.

Overall, this part provides a comprehensive overview of the methodologies employed to acquire and process diverse datasets essential for personalized pedestrian route planning. Through a combination of Python programming and GIS techniques, these data are prepared for subsequent analysis and integration into the route planning framework, facilitating the generation of optimized pedestrian pathways tailored to individual preferences and requirements.

5.3.1 Pedestrian Network Data Acquisition and Processing in GIS

This section outlines the methodology for acquiring and processing pedestrian network data, which forms the backbone of personalized pedestrian route planning. This data includes details about paths, sidewalks, pedestrian crossings, and other pedestrian infrastructure across the urban environment. The following steps describe the acquisition and processing of this data using ArcGIS Pro and Python:

Step I. **Data Acquisition**:

- **Source Identification**: Identify reliable data sources for pedestrian network data, such as local government agencies, open data portals, or geospatial data providers.
- **Data Retrieval**: Retrieve the pedestrian network data, which may be available in various formats such as shapefiles, GeoJSON, or other GIS-compatible formats.

Step II. **Data Cleaning and Preprocessing**:

- **Quality Assessment**: Assess the quality of the data, checking for missing values, duplicate entries, and inconsistencies.
- **Data Cleaning**: Clean the data by removing duplicates, filling missing values, and correcting any inconsistencies.

By following these steps, the pedestrian network data is transformed into a usable and well-structured GIS format that supports the personalized pedestrian route planning system's subsequent stages.

5.3.2 Land Use Data Acquisition and Processing in GIS

Understanding the surrounding environment and its impact on pedestrian experiences is crucial for personalized route planning. In this section, we describe the methodology for obtaining and processing land use data, which provides important context for pedestrian network design. The approach involves several key steps:

Step I. **Gathering Land Use Data**:

We begin by collecting land use data from authoritative sources such as municipal planning offices or public data repositories. This data typically comes in GIS formats like shapefiles, raster datasets, or geospatial databases.

Step II. **Preparing the Data**:

Next, the collected data is assessed for quality and consistency. This may involve cleaning the data to address missing or inaccurate entries and selecting attributes such as land use type (e.g., residential, commercial, recreational) and zoning regulations.

Step III. **Feature Identification**:

Through spatial analysis like proximity analysis factors like parks, green spaces, and cultural sites, etc (all of which enhance the pedestrian experience) identified around each segment.

Step IV. **Integrating Land use Data with Pedestrian Network**:

By overlaying the land use data with pedestrian network data, we associate each path or intersection with its surrounding land use characteristics. This helps us identify how different land uses might influence pedestrian experiences.

By transforming raw land use data into actionable insights, we ensure that the pedestrian network accurately reflects the environment pedestrians will encounter. This process is instrumental in enabling our personalized pedestrian route planning system to recommend optimal routes that blend safety, convenience, and enjoyment.

5.3.3 Streetlight Data Acquisition and Processing in GIS

Streetlight data plays a key role in determining pedestrian safety and visibility, particularly during nighttime journeys. By integrating streetlight data into our system, we can guide pedestrians along well-lit routes, enhancing their safety and overall experience.

The process of acquiring and processing streetlight data and integrating them to the pedestrian network in ArcGIS Pro involves several key steps:

Step I. **Locating Data Sources**:

To begin, we seek out sources of streetlight data from local government agencies, utility companies, and transportation departments. These sources typically offer data in GIS-compatible formats such as shapefiles or GeoJSON.

Step II. **Data Cleaning and Verification**:

After obtaining the data, we take care to verify its accuracy and completeness. This involves cross-referencing with other data sources and field observations. Any inconsistencies, duplicates, or missing values are addressed to ensure high-quality data.

Step III. **Spatial Analysis and Integrating Streetlight Data with the Pedestrian Network**:

A Snap Geoprocessing tool in ArcGIS Pro is used to align streetlight points with the corresponding network edges. This step ensures that the spatial location of streetlights accurately reflects their impact on the pedestrian network, enabling us to extract the number of streetlights per segment for subsequent calculations.

Step IV. **Safety Ratio Calculation**:

In this stage, the Safety Ratio is computed by dividing the number of streetlights associated with each network segment by the segment's length. The resulting Safety Ratio value is then added as a new field in the streetlight GIS layer's attribute table. This measure provides a quantifiable indicator of route safety, with higher values reflecting better lighting conditions and, by extension, enhanced pedestrian safety.

By carefully integrating streetlight data with the pedestrian network, we create a more comprehensive and safety-conscious routing system. This leads to safer and more enjoyable walking experiences, particularly for nighttime travellers.

5.3.4 Digital Elevation Model Acquisition and Processing in GIS

This section explains the approach for acquiring and processing digital elevation model (DEM) data in GIS, which is crucial for understanding the terrain and slopes pedestrians encounter on their journey. The process can be divided into five main steps:

Step I. **Data Acquisition**:

We begin by finding and selecting sources of DEM data that cover our study area and provide the required level of detail. We then obtain the data either by downloading it or accessing it through GIS platforms.

Step II. **Data Preparation**:

Once the DEM data is obtained, we perform quality assurance checks to ensure its accuracy. We may adjust the data's resolution or align its projections to match our other datasets for consistency.

Step III. **Terrain Analysis**:

Using DEM data and ArcGIS Pro Spatial Analysis, we generate a raster slope layer in percentage, providing insights into terrain variations and distinguishing between steep and flat areas.

Step IV. **Integrating Slope Data with the Pedestrian Network**:

The average slope percentage for each network segment is calculated, then extracted and seamlessly incorporated into the pedestrian network using Zonal Statistics of ArcGIS Pro. This integration ensures a comprehensive representation of slope variations across the study area, enhancing the accuracy of route analysis and decision-making.

These steps help us use DEM data to design pedestrian routes that take into account terrain and elevation changes, resulting in safer and more efficient paths for pedestrians.

5.4 Multi-Dimensional Network Module

In the integration of variable/attribute data that are used in calculating Safety, Attractiveness, Accessibility, and Comfort into the pedestrian road network, a meticulous approach is adopted to ensure the holistic enrichment of the network with multi-dimensional attributes. Leveraging spatial joins and attribute linkage in ArcGIS Pro, Safety data, derived from street lighting infrastructure databases, is spatially correlated with road segments to quantify pedestrian visibility factors. Attractiveness data such as parks, museum, etc., sourced from landuse datasets of urban and natural landmarks, is spatially linked to the nodes of the network to enhance route planning by prioritizing aesthetically pleasing routes. Accessibility data include length of each segment calculated through ArcGIS Pro geometric measure tool, provides insights into pedestrian-friendly pathways by quantifying road distances between key destinations. Comfort data, obtained from digital elevation models, enriches the network with slope attributes, facilitating the identification of routes with gentle gradients. This integrative approach fosters a comprehensive understanding of pedestrian navigation preferences and sets the stage for optimized route planning.

Figure 5.2 illustrates the symbolic architecture of the data integration in the multi-dimensional network model

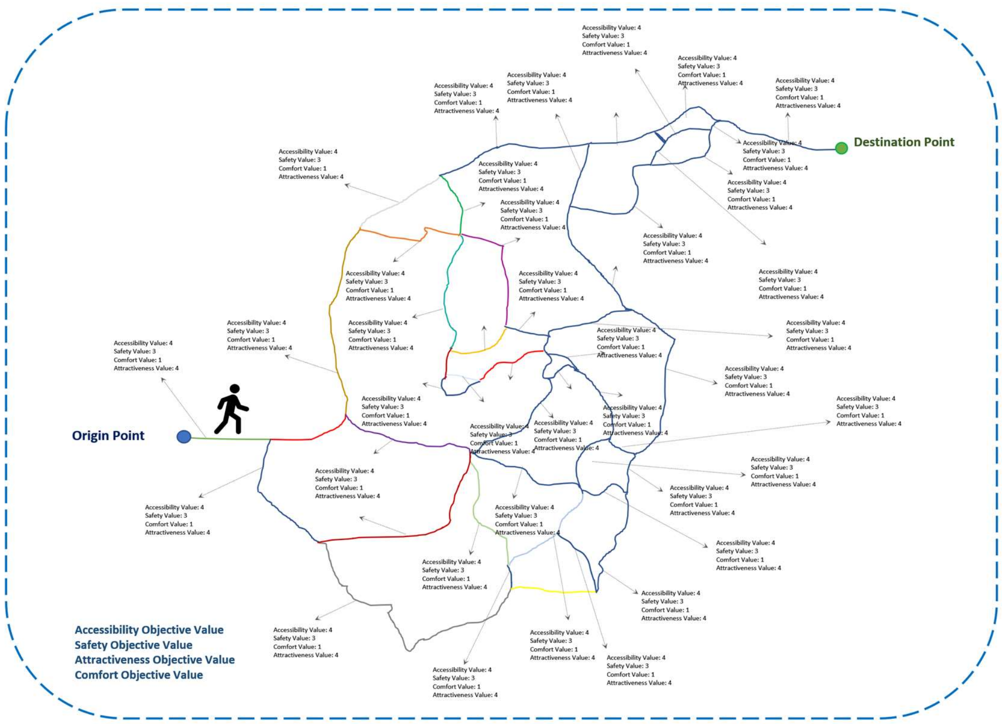


Figure 5.2 A symbolic representation of data integration to each segment

5.4.1 Steps for GIS Network Conversion to Graph Data Structure in Python:

The next step involves converting the enriched GIS-based pedestrian network into a graph data structure, which is essential for computational efficiency in route optimization. This transformation requires defining network nodes (intersections and key waypoints) and edges (road segments) while preserving the multi-dimensional attributes—Safety, Accessibility, and Comfort—assigned to each segment and

Attractiveness assigned to each node. The resulting graph is then structured with adjacency lists or matrices, enabling efficient pathfinding algorithms to analyze trade-offs between conflicting objectives and generate optimal pedestrian routes.

To convert the enriched GIS pedestrian network into a graph data structure, a structured process is followed using Python libraries such as networkx, geopandas, OSMNX and pandas. The conversion begins with loading the GIS data, typically stored in CSV or shapefile format, containing nodes (intersections, waypoints) and edges (road segments). The nodes dataset includes coordinates and landuse attributes, while the edges dataset stores connectivity details and multi-dimensional attributes like Safety, Accessibility, and Comfort.

Step I. **Load GIS Data:**
Read nodes and edges datasets using pandas.read_csv() or geopandas.read_file() if working with shapefiles.

Step II. **Initialize the Graph:**
Create an empty networkx.Graph() with an appropriate coordinate reference system (CRS).

Step III. **Add Nodes:**
Iterate through the nodes dataset, adding each point to the graph with its attributes such as geographic coordinates (x, y) and landuse information.

Step IV. **Add Edges:**
Iterate through the edges dataset to define road segment connections between nodes, incorporating relevant attributes like segment length, mean slope, and visibility based on safety ratio.

Step V. **Validate and Optimize the Graph:**
Ensure proper connectivity and remove any isolated nodes. Convert the graph into an adjacency list or matrix format for efficient computation in later route optimization steps.

By structuring the network as a graph, the pedestrian routing model can efficiently leverage graph-based algorithms such as Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO) to generate optimal routes based on diverse pedestrian preferences.

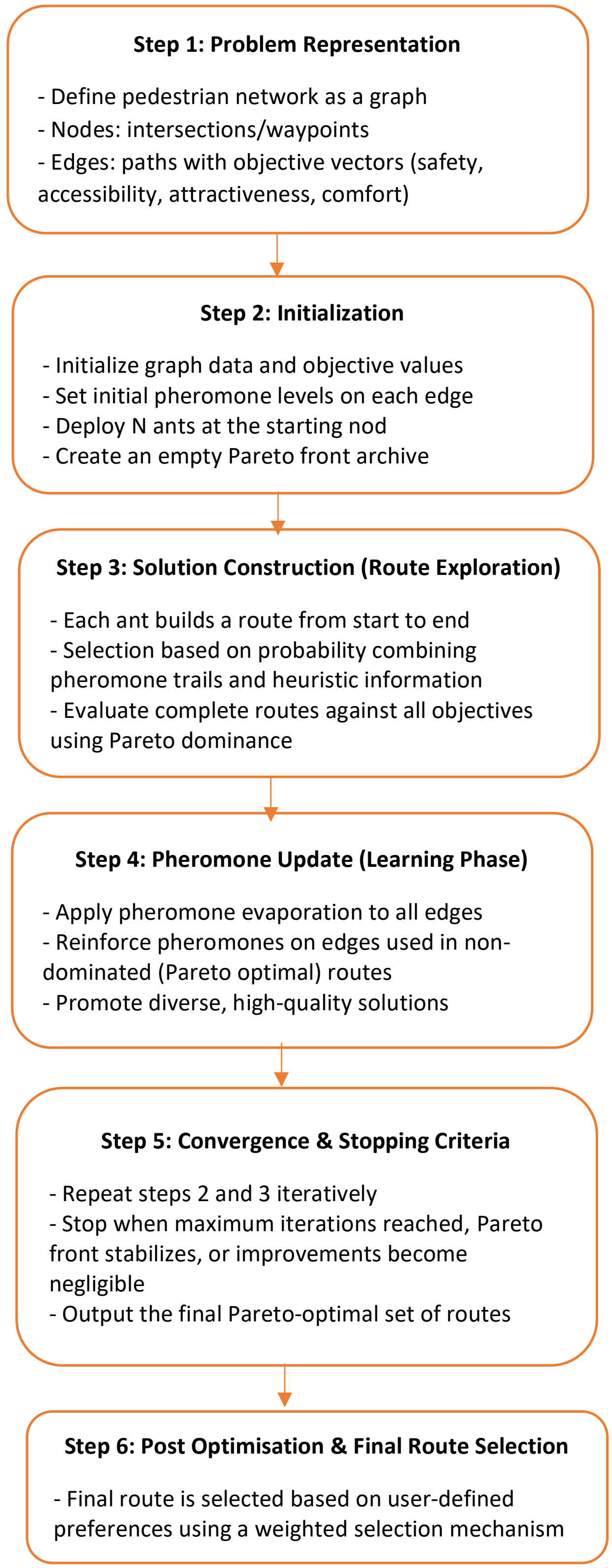
5.5 Algorithmic Solution & Architecture

This section outlines the algorithmic solution and architecture that form the core of our personalized pedestrian route planning system.

- **Section 5.5.1** describes the overall optimization process using PB-MOACO and highlights our contributions in refining and adapting the algorithm to address the specific challenges of pedestrian navigation.
- **Section 5.5.2** delves into the concept of the Pareto-optimal set, providing the mathematical formulation that underpins our multi-objective optimization approach.
- **Section 5.5.3** presents the post-optimization methodology for final path selection, where user-defined preferences are integrated to refine the Pareto set into a single, actionable route recommendation.

Together, these subsections provide a comprehensive overview of our algorithmic framework, ensuring both robust multi-objective optimization and personalized decision-making in pedestrian route planning.

Figure 5.3 Diagram of Algorithm Structure & Optimisation Process



5.5.1 PB-MOACO Optimization Engine Architecture

Building on the well-established foundation of Ant Colony Optimization (ACO) (Dorigo & Stützle, 2003) and its multi-objective extensions (Dorigo & Stützle, 2019; López-Ibáñez & Stützle, 2012), we have developed a customized Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO) framework for pedestrian route planning. Our framework is specifically tailored to address the urban context by integrating four conflicting objectives: safety (street visibility), accessibility (distance), attractiveness (urban land-use types), and comfort (slope percentage).

Unlike previous applications of PB-MOACO in fields such as logistics, traffic management, and network design (Abolhoseini & Sadeghi-Niaraki, 2018; Caramia & Dell'Olmo, 2008; Luo et al., 2024), our approach incorporates urban-specific constraints—such as maximum path distance, acceptable slope, and minimum safety ratios—directly into the optimization process. This ensures that only feasible, pedestrian-friendly routes are considered.

The following sections detail the steps of our PB-MOACO optimization process, highlighting our key contributions in adapting and refining the algorithm to overcome the unique challenges of pedestrian navigation. These include customizing the heuristic function to reflect real-world urban conditions; integrating hard constraints during the solution construction phase; and implementing adaptive stopping criteria to maintain a diverse Pareto front.

Step 1: Problem Representation

- **Graph Structure:**

Define the problem as a graph-based structure, where:

- Nodes represent decision points or states (e.g., crosswalks, intersections, mid-block waypoints).
- Edges represent available transitions or connections.

- **Multi-Objective Functions & Constraints:**

Each edge is evaluated using objective functions for safety, accessibility, attractiveness, and comfort.

- Hard Constraints: Define and embed constraints (e.g., maximum acceptable path distance, maximum slope percentage, minimum safety ratio) into the objective function or as feasibility checks. If a candidate edge or route violates a hard constraint, it is either discarded or assigned a heavy penalty.

Details of Problem representation discussed at Chapter 4, Section 4.4.

Our Contribution:

- In our application, the graph is constructed from detailed GIS data. We adapt this step by ensuring that nodes represent critical pedestrian decision points (e.g., crosswalks, intersections, and mid-block waypoints) and that edges capture specific attributes such as sidewalk quality, crosswalk availability, and local safety factors.
- We design the formula for the four objective functions (safety, accessibility, attractiveness, comfort) to reflect urban nuances, such as variations in street lighting, land-use diversity, and terrain gradients.

Step 2: Initialization:

- **Graph Initialization:**
    - Import GIS data for pedestrian pathways and construct the graph G=(V, E), where each edge is annotated with multi-objective attributes and associated constraint limits.
    - Assign initial pheromone levels τ(i,j) to all edges.
    - Define the heuristic function $\eta_{(i,j)}$ based on problem-specific knowledge, incorporating both multi-objective attributes and constraint checks.
- **Ant Colony Initialization:**
    - Initialize the population N Ants to explore the solution space.
    - Each ant starts from an origin node and constructs a route to the destination node, immediately discarding any edge that violates a hard constraint.

- **Pareto Front Initialization:**
  - Create an empty external archive to store only non-dominated and feasible solutions (i.e., routes that satisfy all hard constraints).

Our Contribution:

- Beyond the standard initialization of pheromone levels and ant deployment, we customize the heuristic function to incorporate pedestrian-specific factors and constraint checks, making it more reflective of actual urban conditions.

  In addition, the initial pheromone values can be adjusted based on preliminary analyses of urban corridors known for either high safety or scenic value.

Step 3: Solution Construction (Route Exploration):

- **Route Construction:**

Each ant incrementally builds a solution using a probabilistic path selection mechanism based on pheromone trails and heuristics.

- **Path Selection with Constraints:**
  - The transition probability for an ant moving from node i to node j is computed as shown in Equation 5.1:

$$P(i,j) = \frac{[\tau_{(i,j)}]^{\alpha}[\eta_{(i,j)}]^{\beta}}{\sum_{k\in \text{ available edges}} [\tau(i,k)]^{\alpha}[\eta(i,k)]^{\beta}} \quad (5.1)$$

Where:

- $P(i,j)$ is the probability of selecting edge (i,j)
- $\tau_{(i,j)}$is the pheromone level on edge (i, j)
- $\eta_{(i,j)}$is the heuristic function (combining the four objectives)
- α controls pheromone influence
- β controls heuristic influence
- $\sum_{k\in \text{ available edges}}$ The denominator normalizes probabilities.

  - **Constraint Check:** Before an edge is considered, the algorithm verifies that it meets all hard constraints (e.g., if the segment's length would cause the overall route to exceed a maximum distance, or if the slope exceeds the acceptable limit). If an edge violates a constraint, it is excluded from the available set (or its heuristic value is penalized).

- **Multi Objective Route Evaluation & Pareto Dominance:**
  - Once a complete route P is constructed, it is evaluated across all objectives.
  - The resulting objective vector F(P) is compared using Pareto dominance, but only among routes that meet the constraints.
- **Updating the Pareto Archive:**
  - Feasible routes that are non-dominated are added to the Pareto archive.
  - Routes violating hard constraints are removed or penalized to ensure the Pareto front represents only acceptable trade-offs.

Our Adjustment / Contribution:

- Fine-tune parameters (α and β) to balance exploration of feasible routes while ensuring constraint adherence.
- Our process Emphasize diverse trade-offs (e.g., short direct routes versus scenic, comfortable alternatives) while filtering out infeasible candidates.

Step 4: Pheromone Update (Learning)

The pheromone update reinforces high-quality solutions while allowing exploration.

1. Pheromone Evaporation (Exploration Mechanism):

- Reduce pheromone levels to avoid premature convergence (Equation 5.2)

$$\tau_{(i,j)} = (1-\rho) * \tau_{(i,j)} \tag{5.2}$$

where ρ is the evaporation rate ($0 < \rho < 1$)

2. Pheromone Deposit Based on Pareto-Optimal Routes:

- Only non-dominated routes contribute to pheromone reinforcement (Equation 5.3):

$$\tau_{(i,j)} = \tau(i,j) + \sum_{S \in P} \frac{1}{\sum_{o=1}^{k} f_o(S)} \tag{5.3}$$

where P is the set of non-dominated solutions.

3. Adaptive Reinforcement:

- Routes with distinct trade-offs among the objective functions are prioritized.
- Ensures users get a variety of route options rather than a single best path.

Our Adjustments:

- We adapt the pheromone update rules to account for the dynamic nature of urban environments. By fine-tuning the evaporation rate (ρ) and the reinforcement function, the algorithm can dynamically respond to changes such as temporary obstructions or improvements in infrastructure.
  The adaptive reinforcement mechanism prioritizes routes offering distinct trade-offs, ensuring that users receive a diverse set of alternatives.

Step 5: Iteration and Convergence:

The process of solution construction and pheromone updating is repeated over multiple iterations. The algorithm terminates when:

- Maximum number of Iterations Reached, or
- Pareto Front Stabilization (no significant updates over multiple iterations)
- Diversity Criteria Met (ensuring solution variety)

Our Adjustment:

- The iterative process is calibrated to converge only when the Pareto front stabilizes and maintains diversity, ensuring that the final set of solutions truly reflects the range of pedestrian preferences.

- Our adjustment includes dynamic stopping criteria that can adjust based on real-time feedback from pilot studies or simulation data.

5.5.2 Pareto-Optimal Set (Mathematical Formulation)

The algorithm finally returns a set of non-dominated pedestrian routes, allowing decision-makers to choose paths based on their preferred trade-offs. For example:

1. **Route A:** High safety, moderate attractiveness, longer distance, less comfy
2. **Route B**: Moderate safety, highly attractive, shortest path, higher comfort
3. **Route C:** Balanced safety, comfort, and accessibility & attractiveness

➢ **Pareto-Optimal Mathematical Expression:**

The **Pareto-optimal set** represents solutions where no single objective can be improved without degrading at least one other objective. For a solution P, it is Pareto-optimal for maximization if and only if:

$\nexists P' \in \mathcal{S}$, such that $\forall i \in [1,2,\ldots,m], f_i(P') \geq f_i(P)$ and $\exists j \in [1,2,\ldots,m], f_j(P') > f_j(P)$, where:

- $\mathcal{S}$: The set of all feasible solutions (all paths satisfying the constraints).
- $f_i(P)$: The value of the i^{th} objective function for solution P.
- m : The total number of objectives.

Explanation (where we maximize the objective functions):

- A solution P' dominates P if P' is no worse in all objectives ($f_i(P') \geq f_i(P)$) and strictly better in at least one objective ($f_j(P') > f_j(P)$).
- The Pareto-optimal set includes all solutions that are not dominated by any other solution in $\mathcal{S}$.

5.5.3 Post Optimisation Methodology for Final Path Selection

After generating the Pareto-optimal set, a post-optimization user preference formula designed to select the final solution from the suggested pareto-optimal solution set. This step incorporates user-defined weights or preferences for each objective and ensures that the final recommendation aligns with specific pedestrian needs while maintaining overall optimality in terms of safety, accessibility, attractiveness, and comfort.

Here's the complete mathematical formulation and methodology steps for the **post-optimization** process:

Step 1: Define the Normalized Objective Functions

Let the normalized objective function values for each pathP_i be represented as follows:

For path $P_i$and objective j, the normalized objective function is shown in Equation 5.4:

$$fj'(P_i) = \frac{f_j(P_i) - f_{i,min}}{f_{j,max} - f_{i,min}} \qquad (5.4)$$

Where:

- $f_j(P_i)$: Original value of objective function j for path P_i,
- $f_{i,min}$and $f_{j,max}$: Minimum and maximum values of objective j across all paths in the Pareto front.

Step 2: Weighted Sum of Objectives

After normalization, each objective function value is assigned a weight according to the pedestrian's preferences or the importance of that objective.

Let the weight for objective j be denoted as w_j. The weights $w_j$must satisfy:

$$\sum_{j=1}^{n} w_j = 1 \qquad (5.5)$$

Where:

- n is the number of objectives.

The overall score $S(P_i)$ for path P_i is the weighted sum of the normalized objective values (Equation 5.6):

$$S(P_i) = \sum_{j=1}^{n} w_j \ . \ fj'(P_i) \qquad (5.6)$$

Where:

- $S(P_i)$: Total score of path P_i,
- w_j: Weight assigned to objective j,
- $fj'(P_i)$: Normalized value of objective j for path P_i.

Step 3: Selection of Final Path

Once the weighted sum of objectives has been computed for all paths in the Pareto front, the final path P_{final} is selected based on the highest score using Equation 5.7:

$$P_{final} = \arg \quad max_{Pi \in Pareto\ Front} \ S(P_i) \qquad (5.7)$$

Where:

- P_{final}: The final selected path,
- Pareto Front: The set of Pareto optimal paths,
- $S(P_i)$: Total score of path P_i.

➢ **Summary of Complete Mathematical Formulation of Post-Optimization**

$$Objective\ Function\ Normalization: fj'(P_i) = \frac{f_j(P_i) - f_{i,min}}{f_{j,max} - f_{i,min}}$$

$$Weighted\ Sum\ for\ Final\ Score: S(P_i) = \sum_{j=1}^{n} w_j \ . \ fj'(P_i)$$

$$Path\ Selection: \ P_{final} = \arg \quad max_{Pi \in Pareto\ Front} \ S(P_i)$$

The path P_{final} is selected as the one that maximizes the weighted sum of the normalized objective functions while satisfying any constraints defined by the user.

This process allows for the final selection of a path after optimization based on the relative importance of different objectives and any additional constraints provided by the user. Let me know if you'd like to further customize the formulation or discuss specific use cases!

➢ **Key Advantages of This Approach:**

- **True Multi-Objective Nature:**
  - Preserves all objectives throughout the search process.
  - Considers diverse trade-offs for a balanced optimization.
- **User-Focused Customization:**
  - Integrates user preferences in the post-optimization phase.
  - Delivers a final route that is both optimal and tailored to the user avoiding confusion and simplifying decision-making.
- **Scalable and Efficient:** It is computationally feasible for large-scale networks and graph network problems.
- **Dynamic Adaptation:** The algorithm adjusts to changes in urban environments, such as new construction or road closures.

Figure 5.3 illustrates the six steps of the PB-MOACO optimization process in our proposed multi-objective pedestrian route planning system, highlighting its robust and dynamic capabilities in optimizing routes that cater to modern urban mobility challenges.

5.6 Overview on Algorithmic Solution for Comparison Purposes

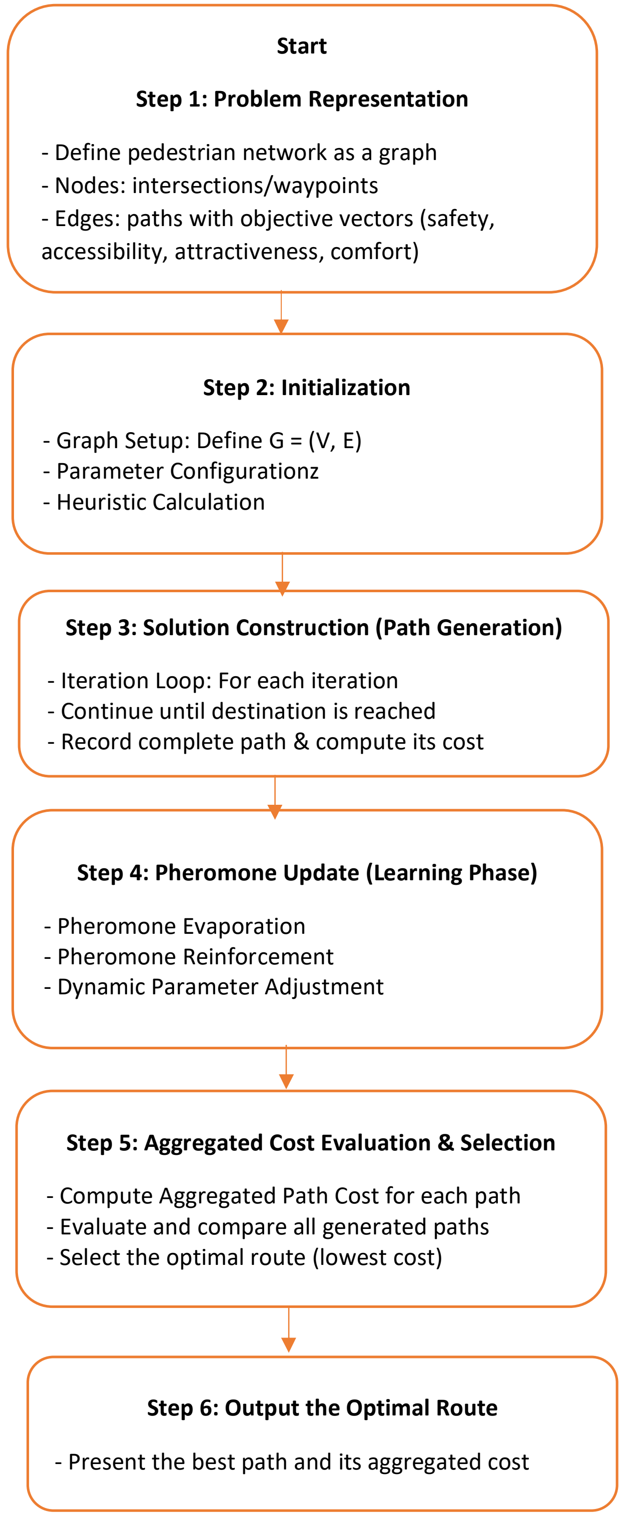
To compare and evaluate the results obtained by PB-MOACO, we employ another variant of ACO which is MOACO via Weighted (Objectives) Aggregation and Dijkstra approach as a benchmark algorithms**.** While MOACO-WA approach combines multiple objectives into a single aggregated function via a well define Heuristic function, Dijkstra mostly focus on extraction of shortest path between origin and destination without considering other objectives

5.6.1 MOACO-WA Optimisation Process

To compare and evaluate the results, we employ, adjust and customised another variant of ACO which is MOACO via Weighted (Objectives) Aggregation as a benchmark algorithm. This approach combines multiple objectives into a single aggregated function via a well define Heuristic function, allowing for a comparative evaluation of results against the Pareto-based MOACO. The use of MOACO-WA enables a comprehensive assessment of solution quality, contributing to a more effective and user-centric pedestrian route planning system. allowing for a comparative evaluation of results against the Pareto-based MOACO. The key adaptations for using this algorithm framework in our study discussed at next section, Optimisation Process.

Following comprehensive optimisation process extends the normal ACO by integrating a weighted aggregation of multiple objectives (MOACO-WA), ensuring that the final selected route provides a balanced and desirable experience for urban travelers. Figure 5.4 represent MOACO-WA functional steps in the system.

Figure 5.4 MOACO-WA Optimisation Process



- **MOACO-WA Optimisation Process**

Step 1: Initialization

- **Graph Setup:**

  Define the urban network as a graph G = (V, E) where vertices V represent intersections, points of interest, and key junctions, and edges EEE represent the connecting paths.

- **Graph Setup:** **Initialize Parameters**

Equation 5.8 defines the user preference weights:

$$\mathrm{W}_{Safety} + \mathrm{W}_{Comfort} + \mathrm{W}_{Accessibility} + \mathrm{W}_{Attractiveness} = 1 \qquad (5.8)$$

- **Parameter Configuration:**

  Set initial parameters:

  - **Pheromone levels** on each edge are uniformly initialized.
  - **User Preferences:** Define weights for each objective (if not inherently captured in the cost function) for Safety (street visibility), Accessibility (path length), Attractiveness (urban landuse scores), and Comfort (mean slope scores).
  - **ACO Parameters:** Set values for α (influence of pheromone), β (influence of heuristic information), and the pheromone evaporation rate.

- **Heuristic Calculation:**

  Compute the heuristic value for each edge (i,j). This value integrates the four objectives by considering how well each edge meets safety, comfort, distance, and attractiveness criteria as shown in Equation 5.9. For instance, an edge's heuristic might be inversely related to its calculated path cost.

$$\eta(\mathrm{i},\mathrm{j}) = (\mathrm{W}_{Safety} \cdot \mathrm{Sa}_{ij}) + (\mathrm{W}_{Comfort} \cdot \mathrm{Co}_{ij}) + (\mathrm{W}_{Accessibility} \cdot \frac{10^6}{D_{ij}}) + (\mathrm{W}_{Attractiveness} \cdot \mathrm{At}_{ij}) \qquad (5.9)$$

Where:

- W_{Safety}, W_{Safety}, W_{Safety}, W_{Safety}, are user-defined weights for Safety, Comfort, Accessibility, and Attractiveness
- Sa_{ij} = Normalized Safety Score for edge (i, j).
- Co_{ij} = Normalized Comfort Score for edge (i, j).
- $\frac{10^6}{D_{ij}}$ = Normalized inverse distance for edge (i, j).
- At_{ij} = Normalized Attractiveness Score for edge (i, j).

Purpose:

- A higher η(i, j) value makes the edge more likely to be selected by ants.
- This heuristic is used in Step 2 (Path Construction) to compute transition probabilities.

Step 2: Constructing Solutions (Path Generation)

- **Iteration Loop:**
  For a predetermined number of iterations (or until convergence):
- **Ant Deployment:**
  Deploy a number of virtual ants (agents). Each ant starts from the designated start node.
- **Path Construction:**
  Each ant builds a complete path from the start to the end node:
    - At each node u, the ant considers the available edges (u,v).
    - **Transition Probability:** The probability of moving from node u to v is computed using Equation 5.10:

$$P(i,j) = \frac{[\tau_{(i,j)}]^{\alpha}[\eta_{(i,j)}]^{\beta}}{\sum_{k\in \text{available edges}} [\tau(i,k)]^{\alpha}[\eta(i,k)]^{\beta}} \tag{5.10}$$

Where:

- $P(i,j)$ is the probability of selecting edge (i,j)
- $\tau_{(i,j)}$ is the pheromone level on edge (i, j)
- $\eta_{(i,j)}$ is the heuristic function (combining the four objectives)
- α controls pheromone influence

- β controls heuristic influence
- $\sum_{k\in \text{available edges}}$ The denominator normalizes probabilities.

- **Route Completion:**
  Continue this process until each ant reaches the destination. Record the complete path and calculate its aggregated cost using the defined Path Cost function.

Step 3: Pheromone Update and Adaptation

- **Pheromone Evaporation (Forgetting Bad Paths):**
  After all ants have completed their paths in the current iteration, the pheromone levels on all edges are reduced to simulate evaporation, preventing premature convergence on suboptimal paths.

$$\tau_{i,j}^{(t+1)} = (1-\rho)\cdot\tau_{i,j}^{(t)} \qquad (5.11)$$

$Where$:

$\tau_{i,j}^{(t+1)}$ is the updated pheromone level after evaporation.

$\tau_{i,j}^{(t)}$ is the pheromone level on edge (i,j) at iteration

ρ is the evaporation rate ($0 < \rho < 1$, typically around 0.1 to 0.5).

- **Pheromone Reinforcement:**
  Edges belonging to high-quality (i.e., low-cost) paths receive increased pheromone levels. The update is typically proportional to the inverse of the path cost.

$$\tau_{i,j}^{(t+1)} = \tau_{i,j}^{(t)} + \sum_{k=1}^{m} \Delta\tau_{i,j}^{(k)} \qquad (5.12)$$

$$\Delta\tau_{i,j}^{(k)} = \frac{Q}{Path\ Cost_k} \qquad (5.13)$$

$Where$:

m is the number of ants.

$\Delta\tau_{i,j}^{(k)}$ is the pheromone contribution from the $k^{th}\ ant$.

Q is a constant (determines the intensity of reinforcement).

$Path\ Cost_k$ is the total cost of the route found by the $k^{th}\ ant$.

- **Dynamic Parameter Adjustment:**

  In the adaptive (MOACO-WA) version, you may:

  - **Reset Pheromones Periodically:** Encourage exploration by periodically resetting pheromone levels to avoid stagnation.
  - **Adjust Weights and Parameters:** Based on the evaluation of the routes (using a separate evaluation function like evaluate_path), update α, β, and evaporation rates to fine-tune the search process.

Step 4: Aggregated Cost Evaluation and Selection

- **Path Cost Calculation:**

  For each ant's constructed path, calculate the overall cost using the provided Equation 5.14:

$$Path\ Cost = \frac{1}{\epsilon + (W_{Sa} \cdot Sa) + (W_{Co} \cdot Co) + (W_{Ac} \cdot Ac) + (W_{At} \cdot At)} \quad (5.14)$$

Here's a breakdown of the components:

- $W_{Sa}, W_{Co}, W_{Ac}, W_{At}$ are user-defined weights for Safety, Comfort, Accessibility, and Attractiveness, respectively. These values determine the importance of each factor in the optimization process. $Sum = 1$
- Sa = Normalized Safety Score (higher is safer)
- Co = Normalized Comfort Score (higher is more scenic route)
- Ac = Normalized Reverse Distance value $\frac{10^6}{Total\ Distance}$ (higher means shorter)
- At: Normalized Attractiveness Score (higher is more comfortable)
- ϵ is a small positive number (e.g., 0.001) to avoid division by zero.

Why This Formula Works

- All four factors contribute equally to reducing the cost: Higher values of Safety (Sa), Comfort (Co), Accessibility (10^6/D), and Attractiveness (At) lead to a lower cost (better path).
- No factor is given special treatment

- Ensures balance between safety, comfort, accessibility, and attractiveness: User-defined weights still allow customization (e.g., if a user values Safety more, W_{Sa} can be higher).

Step 5: Output the Optimal Route

- **Aggregated Evaluation:**
  Evaluate and compare all generated routes based on their aggregated costs. The lower the cost, the more desirable the route considering safety, comfort, distance, and attractiveness.
- **Final Output:**
  After completing all iterations, select the single best route—the one with the lowest aggregated path cost. This route is deemed optimal based on the multi-objective criteria and user preferences.
- **Result Presentation:**
  The final output includes the final optimal route along with its aggregated cost and parameters values. This ensures that urban travelers receive a balanced recommendation based on preferences at safety, comfort, accessibility, and attractiveness.

5.6.2 Dijkstra's Algorithm: Foundations for Route Planning

Dijkstra's algorithm, developed by Dutch computer scientist Edsger W. Dijkstra in 1956, is a cornerstone of graph theory and pathfinding. It solves the single-source shortest path problem for weighted graphs with non-negative edge weights, making it a critical tool for spatial route planning. In pedestrian navigation, where factors like distance, safety, and accessibility are often prioritized, Dijkstra's algorithm provides a foundational framework for deterministic path computation. While originally designed for abstract graphs, its adaptability to spatial networks—such as urban pedestrian grids—has cemented its relevance in geographic information systems (GIS) and navigation applications. This section introduces Dijkstra's algorithm, its mathematical formulation, and its role in spatial path planning.

- **Mathematical Presentation**

Let a graph $G = (V, E)$ represent a spatial network, where:

- V is the set of vertices (nodes) corresponding to locations (e.g., street intersections),
- E is the set of edges (arcs) representing connections between nodes (e.g., sidewalks or pathways),

Each edge $e_{ij} \in E$ has a non-negative weight w_{ij} denoting the traversal cost (e.g., distance, time, or energy expenditure).

Objective: Find the minimum-cost path from a source node s to a target node t

➢ **Algorithm Steps**

Step 1: Initialization

- Assign a tentative distance $d[v]$ to every node v:

$$d[v] = \begin{cases} 0 & f\ v = s, \\ \infty & otherwise \end{cases} \tag{5.14}$$

- Maintain a priority queue Q ordered by $d[v]$, initialized with all nodes.
- Track the predecessor $\pi[v]$ for each node to reconstruct paths.

Step 2: Iteration

While Q is not empty:

- Extract the node u with the smallest d[u].
- For each neighbor v of u:

$$If\ d[v] > d[u] + wuv,\ update\ d[v] = d[u] + wuv\ and\ \pi[v] = u. \tag{5.15}$$

- Remove u from Q.

Step 3: Termination

The algorithm terminates when t is extracted from Q, yielding the shortest path via backtracking π[t].

Properties:

- **Completeness**: Guarantees optimal paths for connected graphs with non-negative weights.
- **Complexity**: $O(\mid E \mid + \mid V \mid log \mid V \mid)$ with a Fibonacci heap, efficient for sparse graphs.

- **Application to Spatial Path Planning for Pedestrians**

In spatial contexts, Dijkstra's algorithm models urban environments as graphs where nodes and edges encode pedestrian infrastructure. Key considerations include:

1. **Graph Construction**:
   - **Nodes**: Represent accessible points (e.g., crosswalks, building entrances).
   - **Edges**: Encode walkable paths (e.g., sidewalks, staircases) with weights reflecting cost metrics (e.g., length, slope, or perceived safety).
2. **Cost Functions**:
   Pedestrian preferences often require dynamic cost adjustments. For example:
   - $wij = distanceij$ (minimize walking distance),
   - $wij = timeij$ (minimize travel time, incorporating walk speed),
   - $wij = riskij$ (avoid poorly lit areas).
3. **Multi-Objective Limitations**:

While Dijkstra's algorithm optimizes a single objective, pedestrian routing often involves trade-offs between conflicting criteria (e.g., shortest vs. safest path). Extensions like the *weighted sum method* or Pareto-optimal algorithms (e.g., NSGA-II) address this but build on Dijkstra's principles.

Dijkstra's algorithm remains a vital tool for spatial path planning due to its simplicity, efficiency, and guarantee of optimality under static, single-objective conditions. However, its limitations in handling multi-objective pedestrian preferences necessitate advanced techniques, which will be discussed in subsequent sections.

5.7 Methodology for Performance Evaluation of Proposed PB-MOACO

An essential part of any route planning project is evaluating the model's adaptability and performance in practical scenarios. This involves examining how effectively the proposed solutions can cater to diverse pedestrian preferences and adjust to different urban environments.

In this section, we outline the methodology employed to evaluate the performance of route-finding algorithms in meeting the diverse needs of pedestrians across different urban environments within the City of Sydney, Australia. Our approach involves calculating routes for each use case using three distinct algorithms, followed by a comprehensive comparison based on predefined evaluation criteria. Subsequent sections clarify the various aspects of our methodology:

5.7.1 Goals of the Evaluation Approach

The primary goal of this evaluation is to assess the effectiveness of the **Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO)** system for pedestrian route optimization compared to two benchmark algorithms: **Dijkstra** and **Multi-Objective ACO via Weighted Aggregation (MOACO-WA)**. Specifically, we aim to:

- Determine the ability of PB-MOACO to balance multiple conflicting objectives (e.g., safety, attractiveness, comfort, and accessibility).
- Assess whether post-optimization based on pedestrian preferences improves decision-making by selecting an optimal solution from the Pareto front.
- Compare the final route solutions generated by each algorithm in terms of safety, safety, attractiveness, comfort, and accessibility, and overall pedestrian suitability.
- Establish the trade-offs and advantages of a Pareto-based approach versus weighted aggregation and shortest-path techniques.

5.7.2 How Performance Evaluation Works and is Designed for this Study

The evaluation is structured as a comparative analysis of the three algorithms, with a focus on their ability to generate pedestrian-friendly routes. Performance is assessed across multiple criteria:

- **Path Safety based on visibility:** Assesses the route's ability to avoid poorly lit areas, prioritizing brighter and safer paths.
- **Path Attractiveness based on Distance:** Measures the efficiency of the route in terms of distance traveled.
- **Path Attractiveness based on Scenic attribute:** Evaluates the number of urban attractions along the path, contributing to overall satisfaction.
- **Path Comfort based on Mean Slope:** Measures the average slope percentage of the route, prioritizing gentler slopes to enhance comfort.
- **Pedestrian Preference Satisfaction:** Assesses how well each algorithm meets pedestrian preferences across these four key parameters.

The performance evaluation will be conducted using a controlled test environment with real-world pedestrian network data. A set of pre-defined pedestrian scenarios (varying in preferences and locations) will be used to ensure consistency in comparison.

5.7.3 Structure of the Comparison-Based Evaluation Approach

The study follows a structured evaluation framework with three main components:

1. **Route Generation Stage**
    - PB-MOACO generates a **Pareto front** of optimal solutions.
    - MOACO-WA produces a **single solution** by aggregating multiple objectives into a weighted sum.
    - Dijkstra generates the **shortest path** solution (baseline).
2. **Post-Processing & Optimization**
    - PB-MOACO applies **pedestrian preference-based post-optimization** to select the most suitable solution from the Pareto set.
3. **Comparative Analysis**

The results are analyzed using both quantitative metrics and qualitative observations. Quantitative evaluation includes ground truth data such as visibility ratio of the path, total path length, number of high-scored landuses along the route, and average path slope. Qualitative analysis assesses how well the generated routes align with user expectations and preferences.

5.7.4 Rationale for Algorithm Selection in Performance Evaluation

This evaluation approach is justified based on the following:

- **Dijkstra as a Baseline:** Dijkstra's algorithm is a widely used shortest path algorithm and serves as an essential benchmark for comparison. It guarantees finding the shortest route in a weighted graph, making it a reliable reference for evaluating efficiency. Many popular navigation platforms, including Google Maps, still employ Dijkstra or its variants for pedestrian pathfinding due to its deterministic and optimal nature in single-objective routing (Chambers et al., 2020; Petrášová, 2016). Since Dijkstra focuses purely on minimizing distance, it helps highlight the advantages of multi-objective approaches that incorporate safety, comfort, and attractiveness. Comparing against Dijkstra ensures that any improvements in pedestrian route planning are demonstrably superior to a well-established baseline. Furthermore, its widespread adoption in modern navigation systems ensures that our evaluation is grounded in real-world applicability and aligns with industry-standard methodologies (Bast et al., 2016). By using Dijkstra as a baseline, we provide a fair and widely recognized comparison, demonstrating the added value of multi-objective route optimization in pedestrian navigation.
- **MOACO-WA as a Benchmark for Comparison:** MOACO-WA (Multi-Objective Ant Colony Optimization with Weighted Aggregation) is selected as a comparative algorithm because it provides an alternative approach to solving multi-objective pedestrian route planning. Unlike PB-MOACO, which maintains a diverse set of Pareto-optimal solutions, MOACO-WA simplifies the multi-objective problem by combining multiple criteria into a single aggregated function using a weighted sum (Falcón-Cardona et al., 2022). This method is widely used due to its computational efficiency and ease of implementation. However, its fixed-weight approach inherently limits flexibility, as predefined weights may not

accurately reflect varying pedestrian preferences or environmental conditions (Masoumi et al., 2021). By comparing MOACO-WA with PB-MOACO, we highlight the advantages of Pareto-based optimization, which allows dynamic trade-offs between conflicting objectives, ensuring more adaptive and personalized pedestrian route recommendations.

- **Comparing Pareto-Based Selection vs. Weighted Aggregation:** The comparison between Pareto-Based Selection (our proposed approach) and MOACO via Weighted Aggregation is essential to demonstrate the advantages of a truly multi-objective optimization method over a simplified weighted-sum approach. MOACO-WA, while computationally efficient, requires predefined weights to aggregate multiple objectives into a single function (Petchrompo et al., 2022). This rigid weighting scheme may not adequately capture dynamic trade-offs between conflicting pedestrian preferences, such as balancing shorter routes with safer or more comfortable paths (Masoumi et al., 2021). In contrast, our Pareto-Based Selection method maintains a diverse set of optimal solutions without enforcing a fixed priority on any single criterion. This allows for greater flexibility in selecting routes that best match varying user preferences and environmental conditions. By comparing these two approaches, we highlight the limitations of fixed-weight aggregation and showcase the benefits of a Pareto-based strategy in generating more adaptive, pedestrian-friendly routes.
- **Real-World Relevance:** The evaluation is designed with realistic pre-defined pedestrian scenarios, making the results applicable to urban mobility planning, pedestrian safety enhancements, and route optimization applications. Detailed description provided in Chapter 6.6.

5.7.5 Evaluation Process and Implementation Steps

The evaluation follows a systematic process:

Step 1: Data Preparation

- Collect and preprocess pedestrian network data from OpenStreetMap (OSM) or city GIS databases.
- Define related attributes and pedestrian-specific constraints.

Step 2: Performance Metrics Calculation

- Compute actual key evaluation metrics (safety ratio, travel distance, path slope percentage, urban land types and associated attractions) along each path in ArcGIS Pro.

Step 3: Algorithm Execution

- Run PB-MOACO to generate a Pareto front of solutions.
- Apply post-optimization using pedestrian preference weights to extract a single optimized solution.
- Run MOACO-WA to obtain a single solution via weighted aggregation.
- Run Dijkstra's Algorithm for the shortest path solution.

Step 4: Comparative Analysis & Interpretation

- Analyse and compare results across all algorithms.
- Identify the trade-offs between shortest-path efficiency, fixed-weight multi-objective optimization, and Pareto-based selection.
- The importance of personalized pedestrian routing will be demonstrated, showing that a one-size-fits-all approach (Dijkstra, MOACO-WA) may not be ideal for all users.

5.8 Chapter Summary

This chapter details the design and implementation of a personalized pedestrian route planning system that integrates multiple components to deliver optimized walking paths tailored to individual preferences and urban conditions. The system seamlessly combines data acquisition, advanced GIS processing, graph-based modeling, and state-of-the-art optimization techniques to address the diverse needs of urban pedestrians.

➢ **System Overview and Components**

The architecture begins with comprehensive data collection and integration. Diverse spatial datasets—including pedestrian networks, land use, streetlight, and digital elevation models—are acquired from reliable sources and processed using Python and GIS tools. These datasets are harmonized into a unified spatial database, forming the backbone for constructing a multi-dimensional graph that accurately represents the urban environment.

The graph-based module transforms the enriched GIS data into a structured network where nodes represent key decision points such as intersections and crosswalks, and edges capture the connectivity between these points. Each element of the graph is annotated with multiple attributes related to safety, accessibility, attractiveness, and comfort. This holistic representation supports the subsequent optimization processes by enabling efficient evaluation of various route quality factors.

➢ **PB-MOACO Optimization Engine**

At the core of the system lies a customized Pareto-Based Multi-Objective Ant Colony Optimization (PB-MOACO) engine. Building on the well-established foundations of Ant Colony Optimization and its multi-objective extensions, the PB-MOACO framework is specifically adapted for urban pedestrian routing. It addresses four conflicting objectives: safety (enhanced through street visibility), accessibility (via efficient path length), attractiveness (reflecting diverse urban land-use types), and comfort (considering slope percentage).

Key adaptations in our PB-MOACO approach include:

- **Problem Representation:** The urban pedestrian network is modeled as a graph where nodes capture critical decision points and edges are evaluated against multi-objective functions while enforcing hard constraints—such as maximum path distance, acceptable slope, and minimum safety ratios—to ensure feasibility.
- **Initialization and Heuristic Customization:** The algorithm initializes the graph with annotated edges and assigns pheromone levels while employing a custom heuristic function. This function integrates pedestrian-specific factors and constraint checks, allowing the optimization to be more reflective of real-world urban conditions.
- **Solution Construction and Route Exploration:** Ants explore the graph probabilistically, constructing candidate routes while discarding or penalizing edges that violate predefined constraints. Each complete route is evaluated across

the four objectives and compared using Pareto dominance, ensuring that only non-dominated, feasible solutions are retained in an external archive.

- **Pheromone Updating and Adaptive Reinforcement:** The system employs adaptive pheromone update rules to reinforce high-quality solutions while promoting exploration. By fine-tuning evaporation rates and reinforcement strategies, the algorithm dynamically adapts to changes in urban conditions, ensuring a diverse set of optimal routes that balance trade-offs among safety, accessibility, attractiveness, and comfort.
- **Iteration and Convergence:** The iterative process continues until the Pareto front stabilizes and maintains diversity. This dynamic stopping criterion ensures that the final set of solutions accurately reflects the range of pedestrian preferences.

➢ **Post-Optimization and Performance Evaluation**

Once the Pareto-optimal set is obtained, a post-optimization stage incorporates user-defined weights to select a final route that aligns with individual preferences. This personalization process transforms the multi-objective outcomes into a single, actionable recommendation by emphasizing the relative importance of each objective.

For performance evaluation, the system is benchmarked against established algorithms—such as Dijkstra's algorithm and an alternative Multi-Objective Ant Colony Optimization via Weighted Aggregation (MOACO-WA). Comparative analyses and real-world testing validate the robustness and scalability of the proposed approach, confirming its ability to deliver safe, efficient, and enjoyable pedestrian routes.

In summary, Chapter 5 presents an integrated system architecture that not only leverages advanced GIS and graph-based methodologies but also pioneers a customized PB-MOACO optimization engine. This design provides a robust and dynamic solution for personalized urban pedestrian route planning, ensuring that final route recommendations are both optimal and user centric.

CHAPTER 6

SYSTEM IMPLEMENTATION AND EVALUATION

6.1 Introduction

A crucial aspect of this study is to test the adaptability and effectiveness of the developed algorithm in real-world scenarios. This involved assessing how well the proposed solutions could accommodate a wide range of pedestrian preferences and adapt to varying urban landscapes.

In this chapter will first discuss basic GIS network application tools which used for the route system. Next, a demonstration of the system application will be presented by using some case studies based on a pedestrian network in the city of Sydney.

6.2 Study Area Selection

The selection of an appropriate study area is critical for validating the efficacy of the proposed framework. In this study, the Local Government Area (LGA) of the City of Sydney was chosen as the primary experimental site, encompassing an expansive area of 26.15 km^2. The rationale behind selecting this area was multifaceted, primarily driven by its diverse and dynamic landscape composition.

The City of Sydney LGA boasts a rich tapestry of land uses and landscapes, ranging from densely urbanized regions to picturesque coastlines, and vibrant tourist and recreational hubs (see Figure x). This diverse array of environments provides a fertile ground for assessing the adaptability and robustness of the proposed algorithm across various terrains and scenarios.

A paramount consideration in the selection process was the presence of a well-distributed pedestrian network throughout the area. It was imperative to choose a location where pedestrian pathways are intricately woven into the fabric of the urban and natural environment, facilitating comprehensive route planning analyses. Additionally, the study area needed to offer a harmonious blend of built-up areas, verdant green spaces, and notable landscape attractions, thus affording the opportunity to explore multiple facets of route planning under varying environmental conditions.

By selecting the LGA of the City of Sydney as the study area, this research endeavors to leverage the diverse landscape and pedestrian infrastructure to thoroughly evaluate the proposed framework's performance across a spectrum of real-world scenarios.

The Central Business District (CBD), with its dense concentration of commercial buildings and bustling streets, presents challenges of pedestrian congestion and accessibility to amenities. Residential areas exhibit a mix of high-rise apartments and historic precincts, each with its unique pedestrian infrastructure and character. Green spaces like Hyde Park and the Royal Botanic Garden offer opportunities for leisurely strolls and connectivity between neighborhoods. Waterfront areas such as Circular Quay and Barangaroo showcase scenic routes but may also pose navigation challenges due to varied terrain and mixed-use development. Transportation hubs like Central Station serve as pivotal nodes, linking different parts of the city and requiring efficient pedestrian routing solutions. Cultural and educational institutions contribute to the fabric of the city, with pedestrian-friendly precincts inviting exploration and engagement. Understanding the intricacies of these land uses and landscapes is crucial for developing a route planning algorithm that optimizes factors such as walkability, safety, scenery, comfort and individual preferences.

This strategic choice allows us to test the algorithm in a controlled yet varied environment, offering a mix of scenic park routes, bustling streets, and cultural landmarks. By limiting the initial testing ground to this specific area, we can closely monitor and refine our model, ensuring the generated routes are not only optimized for personal preferences but also viable and reliable in a dense urban setting.

Figure 6.1 provides an encompassing overview of the study area utilizing OpenStreetMap (OSM) as a basemap, delineating the geographical extent under scrutiny for the research.

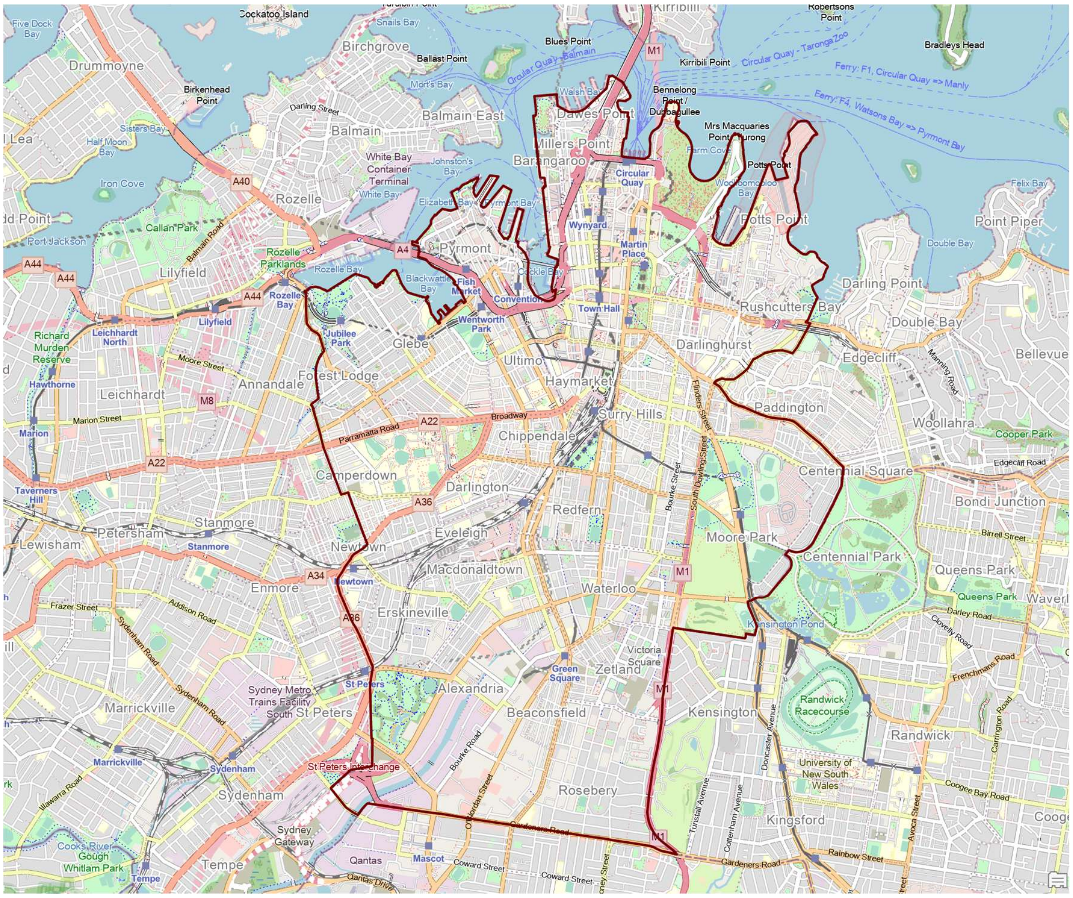


Figure 6.1 Study Area Overview on OpenStreetMap Basemap.

6.3 Exploratory of Spatial Datasets and Analysis

Understanding the intricate spatial characteristics and infrastructure components of urban environments is paramount for effective urban planning and pedestrian mobility.

This section provides an overview of key spatial datasets essential for analyzing pedestrian mobility and urban infrastructure within the City of Sydney. We begin by introducing the Pedestrian Network of the City of Sydney (Section 6.3.1), which encompasses pedestrian pathways, footpaths, and crossings crucial for pedestrian connectivity.

Next, we discuss the Classified GIS Land Use Layer of the City of Sydney (Section 6.3.2), highlighting the spatial distribution of land use categories such as residential, commercial, and recreational zones, shaping pedestrian activity patterns.

Following this, we present the Street Lighting Infrastructure in the City of Sydney (Section 6.3.3), focusing on the spatial distribution and illuminance levels of streetlights, vital for enhancing pedestrian safety at night.

Lastly, we introduce the Digital Elevation Model of Sydney City (Section 6.3.4), providing insights into terrain elevation and topographic features, guiding pedestrian route planning in areas with varied terrain.

These spatial datasets lay the foundation for further analysis and exploration in subsequent sections, aiming to understand pedestrian mobility patterns, urban infrastructure dynamics, and the spatial nuances of the City of Sydney.

It is important to note that all spatial datasets presented in these sections have undergone extensive preprocessing steps, including data cleaning, clipping, reprojection, and other necessary transformations. The results presented here are the culmination of meticulous data preparation efforts aimed at ensuring data integrity, consistency, and compatibility for subsequent analysis and interpretation.

6.3.1 Results of Pedestrian Network Processing in the City of Sydney

The City of Sydney Road Network serves as the backbone of urban mobility, facilitating the movement of pedestrians across diverse landscapes and built environments.

6.3.1.1 Data Acquisition

In this study, the complete road network dataset from OpenStreetMap (OSM) was utilized to encompass all types of pedestrian pathways, sidewalks, footways, streets, cycleways, tracks, and other relevant infrastructure. OSM is a collaborative mapping platform providing open-access geospatial data.

Due to the incomplete nature of pedestrian-specific network data in OSM, the complete road network dataset from OSM was utilized to ensure comprehensive coverage of pedestrian pathways and associated infrastructure within the City of Sydney.

The dataset includes a comprehensive representation of pedestrian infrastructure, incorporating various types of pathways and road segments:

- **Pedestrian Walkways:** Dedicated pathways for pedestrians, providing safe and accessible routes throughout the urban landscape.
- **Footways and Paths:** Narrow paths and trails traversing parks, recreational areas, and residential neighborhoods, catering to pedestrian traffic.
- **Streets and Roads:** Primary thoroughfares and secondary streets accommodating vehicular traffic, with designated pedestrian sidewalks and crossings.
- **Cycleways and Shared-Use Paths:** Segregated and shared paths for cyclists and pedestrians, promoting active transportation and recreational activities.
- **Specialized Infrastructure:** Unique infrastructure such as steps, bridleways, and tracks, serving specific transportation needs and recreational pursuits.

➢ **Spatial Attributes**

Key spatial attributes embedded within the Complete OSM network dataset include:

- **Segment Geometry:** Geospatial coordinates delineating the geometry of each road segment, facilitating spatial analysis and visualization.
- **Node Geometry:** Geospatial coordinates representing the location of network nodes, essential for network topology analysis and routing algorithms.
- **Segment Classification:** Categorical classification of road segments based on their primary function and usage, enabling researchers to differentiate between pedestrian walkways, vehicular roads, and mixed-use paths.
- **Node Classification:** Categorization of network nodes based on their significance and connectivity within the transportation network, aiding in route optimization and network modeling.

- **Topology Information:** Connectivity and adjacency information highlighting the spatial relationships between road segments and nodes, essential for network analysis and routing algorithms.

6.3.1.2 Processing Results in the Study Area

The outcomes of the methodology outlined above presented below, including visualizations of the extracted pedestrian network, analyses of its spatial characteristics and patterns, and insights gleaned regarding pedestrian mobility within the City of Sydney. Figure 6.2 illustrates the integrated edge and node geometries comprising the Sydney OSM network.

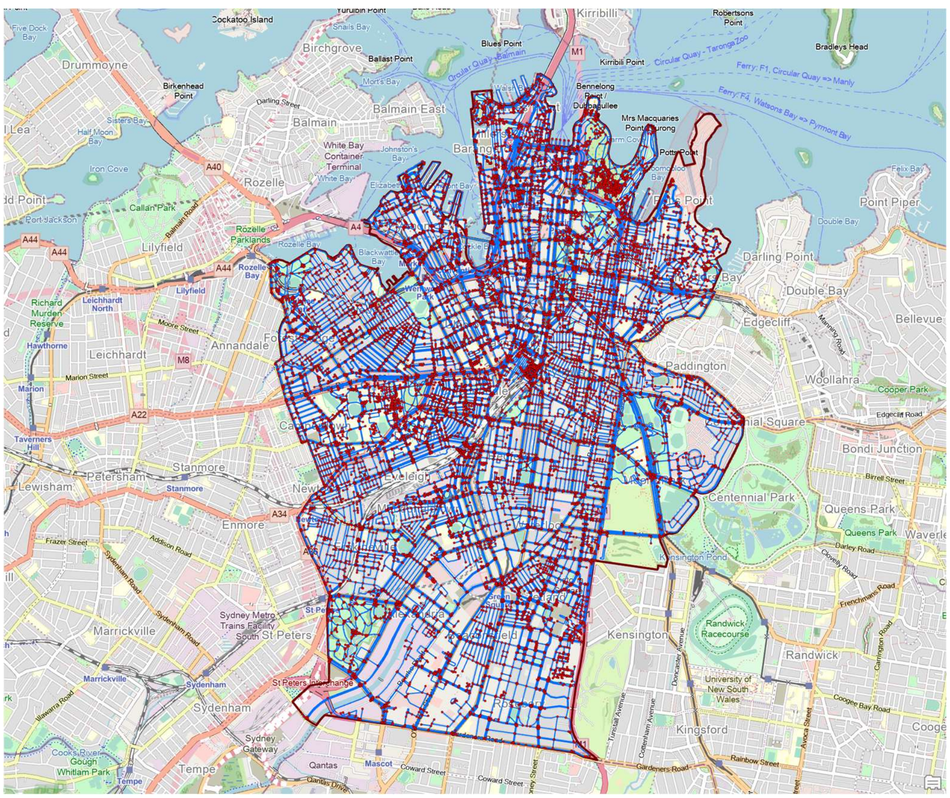


Figure 6.2 Combine edge and node geometries of the Sydney OSM network.

6.3.2 Land Use GIS Layer of the City of Sydney

The Land Use GIS Layer of the City of Sydney is an integral component of the spatial dataset utilized in this study, providing valuable insights into the distribution and significance of various land use categories, particularly in relation to pedestrian mobility and urban accessibility.

6.3.2.1 Data Sources and Acquisition

The land use data utilized in this study was sourced from the NSW Department of Climate Change, Energy, the Environment, and Water. As the authoritative agency responsible for land use planning and environmental management in New South Wales (NSW), the department maintains comprehensive spatial datasets detailing the distribution and classification of land use categories within the City of Sydney and surrounding regions.

6.3.2.2 Spatial Attribute

The Land Use GIS Layer encompasses a diverse range of land use types, each with its own implications for pedestrian activity and urban liveability. In order of importance for pedestrians, these land use types include:

- **Recreation and Culture:** Areas designated for recreational activities, cultural institutions, and leisure amenities, promoting pedestrian engagement and community interaction.
- **National Park:** Pristine natural reserves and protected areas offering scenic vistas, walking trails, and opportunities for outdoor recreation, enhancing pedestrian access to nature and green spaces.
- **Coastal Waters:** Coastal zones and waterfront areas featuring promenades, boardwalks, and recreational facilities, attracting pedestrians seeking waterfront experiences and scenic views.
- **Urban Residential:** Residential neighborhoods and urban villages characterized by walkable streetscapes, pedestrian-friendly amenities, and mixed-use developments, fostering a sense of community and pedestrian vibrancy.
- **Commercial Services:** Central business districts, retail corridors, and commercial hubs offering a diverse array of shops, services, and entertainment venues, stimulating pedestrian activity and economic vitality.
- **Public Services:** Government buildings, educational institutions, healthcare facilities, and civic amenities providing essential services and community resources within walking distance of residents and visitors.

- **Other Conserved Areas:** Protected conservation areas, green belts, and environmental reserves preserving natural habitats and biodiversity, enriching the pedestrian experience with opportunities for exploration and environmental stewardship.
- **Land in Transition:** Areas undergoing urban redevelopment, revitalization, or adaptive reuse, presenting opportunities for pedestrian-oriented design, placemaking, and community engagement.
- **Manufacturing and Industrial:** Industrial zones and manufacturing districts characterized by heavy infrastructure, vehicular traffic, and limited pedestrian amenities, posing challenges for pedestrian safety and accessibility.
- **Highways:** Major arterial roads, expressways, and motorways designed primarily for vehicular traffic, creating barriers to pedestrian mobility and connectivity within the urban fabric.
- **Railways:** Rail corridors, train stations, and transit hubs serving as vital transportation arteries but often presenting barriers to pedestrian movement and access due to safety concerns and infrastructure constraints.

6.3.2.3 Processing Results of GIS Land Use Layer for the City of Sydney

The Classified GIS Land Use Layer incorporates spatial attributes such as polygon boundaries, attribute data, and metadata, enabling spatial analysis, visualization, and decision-making (Figure 6.3). These attributes offer valuable insights into the extent, distribution, and characteristics of each land use category, informing urban planning, development, and policy formulation processes.

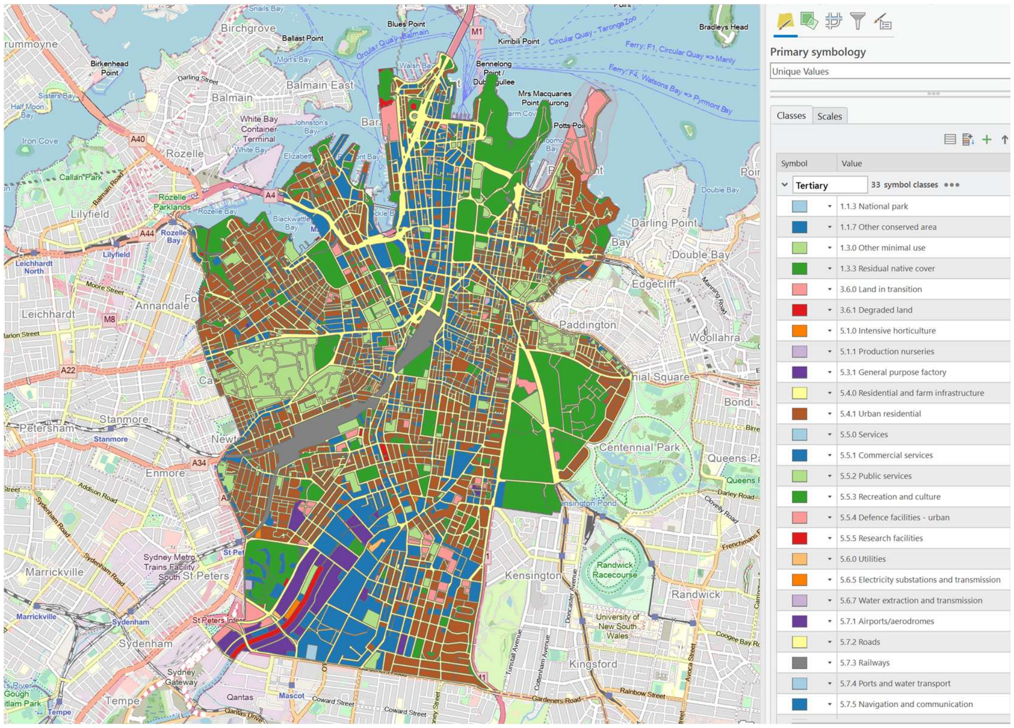


Figure 6.3 The Classified GIS Land Use Layer of the City of Sydney

6.3.2.4 Landuse Ranking for Attractiveness in the Node Data List

Pedestrian walking paths play a crucial role in urban planning and design, shaping the quality of life and mobility options available to residents and visitors alike. From scenic parks to bustling commercial districts, the variety of pedestrian environments reflects the diverse needs and preferences of communities. Understanding the relative attractions of different pedestrian walking path classes is essential for urban planners, policymakers, and designers seeking to create vibrant, accessible, and pedestrian-friendly cities.

In this ranking, we evaluate eleven distinct classes of pedestrian walking paths based on their inherent attractions for pedestrians. Each class represents a unique environment with its own set of characteristics, amenities, and potential for pedestrian enjoyment. By assessing the appeal of these pedestrian walking path classes, we aim to shed light on the factors that influence pedestrian behavior and preferences, informing future urban planning and design decisions.

The ranking considers a range of factors, including natural beauty, recreational opportunities, access to amenities, and safety considerations. Through this comprehensive evaluation, we hope to provide insights into the diverse needs and preferences of pedestrians, as well as guidance for enhancing the attractiveness and functionality of pedestrian environments. Let's delve into the ranking of pedestrian walking path classes and explore the factors that contribute to their appeal for pedestrians.

National Park (Rank: 10): National parks are typically characterized by natural beauty, diverse ecosystems, and recreational opportunities such as hiking trails and scenic views. They offer a serene and peaceful environment for walking, making them highly attractive to pedestrians seeking a connection with nature and outdoor activities.

Recreation and Culture (Rank: 9): Areas designated for recreation and cultural activities, such as parks, plazas, and cultural landmarks, offer opportunities for leisurely strolls, social interaction, and cultural enrichment. These spaces often feature amenities like walking paths, green spaces, and public art, enhancing their appeal to pedestrians.

Coastal Waters (Rank: 8): Coastal areas provide stunning views, refreshing sea breezes, and opportunities for activities like beachcombing and seaside walks. The scenic beauty and recreational potential of coastal waters make them attractive destinations for pedestrians seeking a tranquil and invigorating walking experience.

Urban Residential (Rank: 7): Residential neighborhoods in urban areas offer a mix of residential streets, parks, and local amenities. These areas provide a comfortable and familiar environment for walking, with opportunities to explore diverse architectural styles, community parks, and neighborhood shops.

Commercial Services (Rank: 6): Commercial districts with shops, restaurants, cafes, and entertainment venues can be bustling hubs of activity, attracting pedestrians with the promise of shopping, dining, and entertainment options. The vibrancy and convenience of commercial areas make them appealing destinations for pedestrian activity.

Public Services (Rank: 5): Area’s housing public services such as government buildings, libraries, and community centers may offer pedestrian-friendly amenities like sidewalks, plazas, and landscaped areas. While not typically as leisure-oriented as parks or recreational areas, public service zones provide essential services and infrastructure that may attract pedestrian traffic.

Other Conserved Areas (Rank: 4): Conserved areas such as nature reserves, wildlife sanctuaries, and conservation areas offer opportunities for nature exploration, wildlife viewing, and ecological education. While not as well-known or accessible as national parks, these areas still hold appeal for pedestrians interested in experiencing natural environments and biodiversity.

The rank provided for "Other conserved area" (Rank: 4) reflects its attractiveness to pedestrians relative to the other listed pedestrian walking path classes. While conserved areas such as nature reserves and wildlife sanctuaries offer opportunities for nature exploration and wildlife viewing, there are several reasons why they may not receive a higher rank compared to other categories:

Accessibility: Conserved areas may be located in remote or less accessible locations, requiring significant travel time or logistical challenges to reach. This limited accessibility can reduce their appeal to pedestrians, particularly those seeking convenient or easily accessible walking paths.

Infrastructure: Conserved areas may have limited pedestrian infrastructure, such as trails, boardwalks, or interpretive signage. Inadequate infrastructure can impact the quality and safety of the walking experience, detracting from their overall attractiveness to pedestrians.

Amenities: Unlike urban parks or recreational areas, conserved areas may lack amenities such as restrooms, picnic areas, or visitor centers. The absence of these amenities can limit the comfort and convenience of visitors, affecting their willingness to explore and spend time in the area.

Perception of Restrictions: Some conserved areas may have regulations or restrictions in place to protect sensitive habitats or wildlife, such as designated trails or off-limit areas. While these measures are essential for conservation purposes, they may be perceived as limiting the freedom or spontaneity of visitors, reducing their appeal as walking destinations.

Awareness and Promotion: Conserved areas may have lower visibility or awareness compared to more popular recreational destinations like national parks or urban parks. Limited promotion or marketing efforts can result in fewer visitors and less foot traffic, impacting the overall attractiveness of the area to pedestrians.

While conserved areas offer valuable opportunities for nature appreciation and ecological education, these factors may contribute to their lower rank relative to other pedestrian walking path classes in terms of attractiveness to pedestrians.

Land in transition (Rank: 3): Areas undergoing transition or redevelopment may offer unique opportunities for exploration and discovery. While not always aesthetically pleasing, these areas may feature urban art installations, temporary green spaces, or revitalization projects that draw pedestrian interest.

Manufacturing and industrial (Rank: 2): Manufacturing and industrial zones typically prioritize vehicular traffic and may lack pedestrian-friendly infrastructure. These areas are often characterized by heavy machinery, industrial buildings, and transportation infrastructure, making them less attractive to pedestrians seeking recreational or leisurely walking experiences.

Highways (Rank: 1): Highways are designed for fast-moving vehicular traffic and are inherently unsafe and uninviting environments for pedestrians. They lack pedestrian infrastructure, such as sidewalks and crosswalks, and pose significant safety hazards due to high-speed traffic and limited visibility.

Railways (Rank: 0): Railways are active transportation corridors primarily intended for trains, making them hazardous and unsuitable for pedestrian activity. They are characterized by noise, vibration, and the risk of injury from trains, making them the least attractive option for pedestrians seeking walking paths.

6.3.3 Street Lighting Infrastructure in the City of Sydney

The GIS Layer of Street Lights serves as a valuable resource for urban planners, transportation engineers, and public safety officials in evaluating and optimizing street lighting infrastructure. By analyzing the spatial distribution and characteristics of streetlights, stakeholders can identify areas with inadequate lighting coverage, assess the impact of lighting upgrades or installations on pedestrian safety, and prioritize investment in lighting improvements to enhance nighttime visibility and security for pedestrians and other road users.

The GIS Layer of Street Lights in the City of Sydney provides essential spatial information about the distribution and characteristics of street lighting infrastructure across the urban landscape.

6.3.3.1 Data Sources and Acquisition

The asset owner responsible for the street lighting infrastructure in the City of Sydney is the Ausgrid company (Ausgrid, 2023). As a leading electricity distributor in New South Wales, Ausgrid plays a vital role in managing and maintaining the street lighting network to ensure optimal performance and reliability.

This dataset encompasses the geographic locations and attributes of streetlights within the City of Sydney. The dataset is essential for understanding the coverage and effectiveness of street lighting in enhancing pedestrian safety, visibility, and nighttime mobility.

6.3.3.2 Spatial Attributes

Key spatial attributes included in the GIS Layer of Street Lights dataset comprise:

- **Geographic Coordinates:** Precise location data indicating the spatial distribution of streetlights throughout the city.
- **Attribute Data:** Information about each streetlight, such as its type, asset status, positional accuracy, installation date, and maintenance history, etc enabling detailed analysis and assessment of lighting infrastructure.

6.3.3.3 Processing Results of Streetlights GIS Data in the City of Sydney

Figure 6.4 provides a visual representation of the Street Lighting Infrastructure in the City of Sydney, showcasing the spatial distribution and density of streetlights across different neighbourhoods and urban areas.

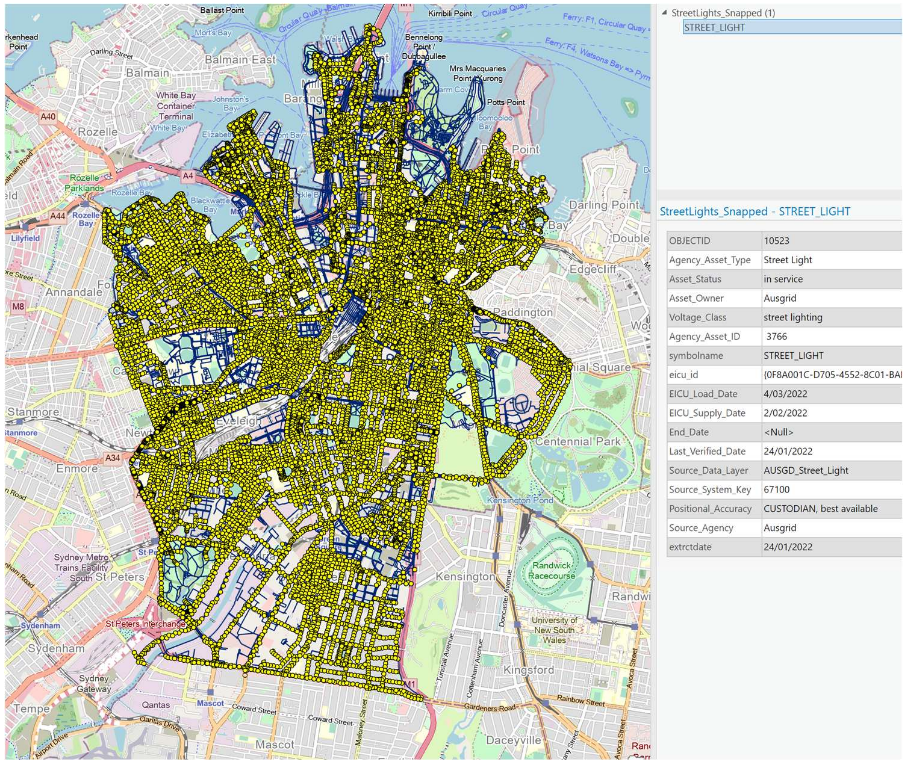


Figure 6.4 Distribution of Street Lights in the City of Sydney

6.3.4 Digital Elevation Model of Sydney City

The Digital Elevation Model (DEM) serves as a critical resource for various applications in urban planning, environmental management, and infrastructure development. By incorporating terrain elevation data into pedestrian route planning algorithms, policymakers, urban planners, and landscape architects can optimize pedestrian pathways, identify suitable locations for pedestrian infrastructure, and mitigate potential hazards associated with steep terrain or elevation changes.

The Digital Elevation Model (DEM) of Sydney City serves as a foundational spatial dataset, providing valuable insights into the topographic characteristics and elevation profiles of the urban landscape. Derived from LiDAR (Light Detection and Ranging) technology and processed into a 5-meter grid resolution, this dataset offers a high-resolution representation of terrain elevation across the City of Sydney and surrounding areas.

6.3.1.3 Data Source

The DEM of Sydney City was sourced from Geoscience Australia, the national geological survey agency responsible for geospatial data collection, management, and dissemination.

6.3.1.4 Spatial Attributes

Key spatial attributes embedded within the DEM dataset include:

- **Elevation Values:** Numeric representations of ground elevation at each grid cell, measured in meters above sea level, enabling quantitative analysis of elevation profiles and terrain features.
- **Slope Percent:** Derivation of slope percentage from elevation data, providing information on the steepness of terrain surfaces and identifying areas of potential pedestrian challenges or accessibility constraints.

6.3.1.5 Processing Results of Digital Elevation Model for Sydney City

Figure 6.5 illustrates the elevational and slope percentage distribution of Sydney City depicted in the Digital Elevation Model (DEM).

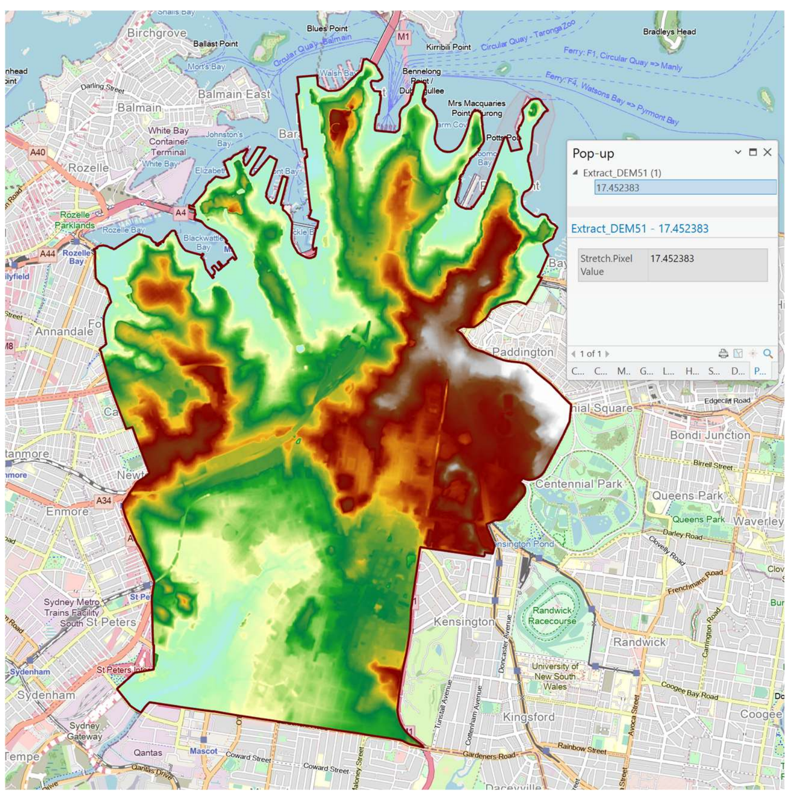


Figure 6.5 Elevational Distribution of Sydney City in the Digital Elevation Model

It's worth noting that all spatial databases used in this study are open-source and were sourced from the publicly available NSW spatial databases.

Table 6.1 succinctly presents the key characteristics of the datasets collected for the study area, along with their respective sources.

Table 6.1 Characteristics of spatial collected datasets for study area.

Spatial Dataset	Source / Acquisition Date	Type	Accuracy	Percentage of Completion
Spatial Road Network	(OpenStreetMap)	Vector (polyline)	1:5000	100%
NSW Administrative Boundaries	(OpenStreetMap)	Vector (Polygon)	Council Administrative Boundaries	100%
Land Use layer	("NSW Landuse 2017,")	Vector (Polygon)	No overall accuracy reported	100%
Digital Elevation Model	"Geoscience Australia" 2015)	Raster (Grid)	5 m (Derived from LiDAR Data)	100%
Street Lighting Infrastructure	Ausgrid (2023)	Vector (Point)		100%

6.4 Integration of All Spatial Parameters with Pedestrian Network

After collecting and processing spatial parameters, such as Safety Ratio, Comfort, and other relevant attributes, we integrate this data into the OpenStreetMap (OSM) network. This integration allows us to create a multi-dimensional graph that encapsulates various aspects of the urban environment and is ready for analysis in Python.

The integration process involves augmenting the OSM network with additional node and edge attributes derived from the spatial data collected. These attributes may include safety scores, comfort ratings, points of interest (POIs), and any other relevant information pertinent to pedestrian or cyclist experience.

Once the integration is complete, we have a comprehensive graph representation of the urban environment, where each node and edge contain a wealth of spatial information. This multi-dimensional graph serves as the foundation for further analysis and optimization tasks aimed at enhancing pedestrian and cyclist mobility, safety, and overall urban experience.

In Python, we can leverage libraries such as NetworkX, GeoPandas, and matplotlib to visualize and analyze the integrated OSM graph. These tools provide functionalities for graph manipulation, visualization, and algorithm implementation, allowing us to conduct various analyses and derive valuable insights to inform urban planning and decision-making processes. Figure 6.6 presents the comprehensive multi-dimensional network of the City of Sydney, showcasing the integration of various spatial parameters.

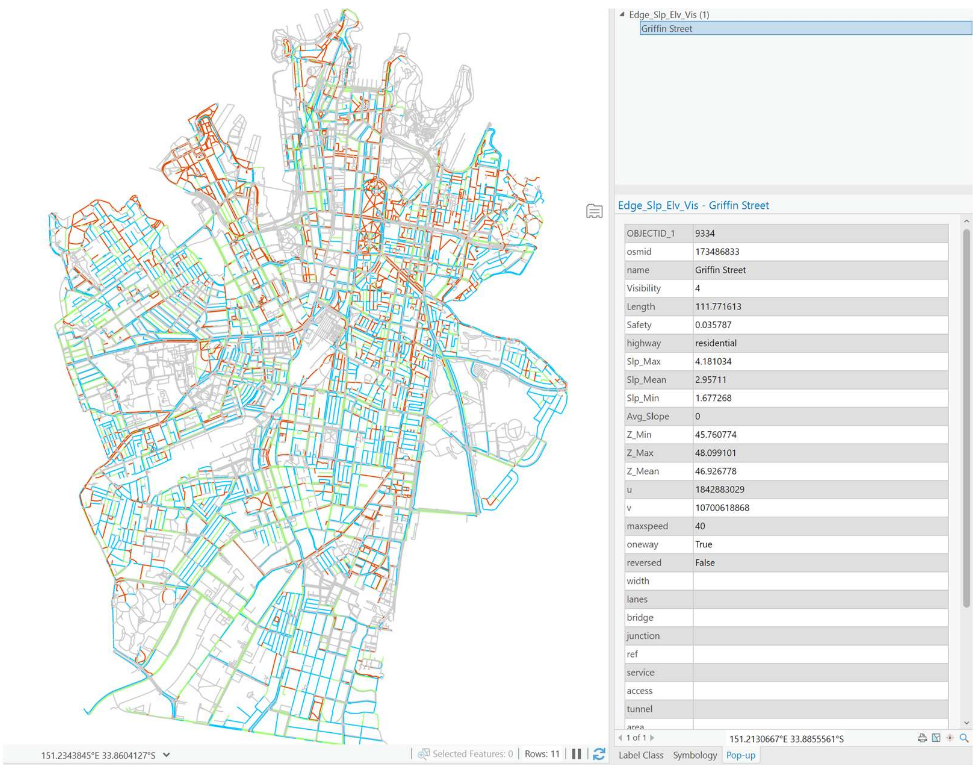


Figure 6.6 Comprehensive multi-dimensional network of the City of Sydney

6.5 Scenario Design for Route-Finding Evaluation in Various Urban Environments

Urban areas exhibit a variety of characteristics, each presenting distinct challenges and opportunities for route planning. From dense city centres with complex road networks to suburban and residential zones with more open spaces, each type of environment affects pedestrian behaviour and preferences.

Well-designed scenarios are essential for assessing the algorithm's effectiveness across different urban environments and pedestrian needs. Although, our system is designed for a wide range of pedestrians and can be used in various scenarios without restrictions, to evaluate the performance and practicality of our route-finding algorithms, this section focuses on developing diverse and representative scenarios.

To design effective scenarios, we decide to account for the following factors:

- **Pedestrian Types:** Our evaluation considers two distinct groups of pedestrians, tourists and commuters, each with unique route preferences and requirements. Tourists may prioritize scenic and culturally rich paths, while commuters typically seek the shortest and most efficient routes.

- **Acceptable Walking Distance:** The distance pedestrians are willing to walk varies based on pedestrian type, individual preferences, and trip purpose. Our system / scenarios account for these variations, ensuring that route recommendations align with realistic walking thresholds for both tourists and commuters.

- **Priority Parameters:** Route selection is shaped by key factors such as accessibility (distance), safety (visibility), comfort (average path slope), and attractiveness (urban land use types). The relative importance of these factors varies depending on pedestrian type and context. Our system / scenarios consider pedestrian preferences, enabling the development of personalized routes that cater to individual needs and enhance the walking experience.

In the next section, we will delve into the details of each use case, specifying the urban environment, pedestrian type, acceptable walking distance, and priority parameters. This information will provide the foundation for creating origin-destination pairs and routes using the developed algorithm.

Following the exploration of the different use cases, the subsequent subsection will present the performance evaluation results. These results will provide insights into the effectiveness and efficiency of the algorithm in addressing the diverse scenarios and preferences encountered across the City of Sydney.

6.6 Use Case 1: Tourists in Sydney Central Business District (CBD)

This use case focuses on tourists navigating the bustling Central Business District (CBD) of Sydney. The primary purpose is to assess the algorithm's ability to provide routes that emphasize cultural and scenic attractions while maintaining safety and comfort. Figure 6.8 shows the origin and destination point of use case one.

Tourists generally prefer longer walks, so the scenario aims to offer the best paths connecting popular landmarks, shopping districts, and other points of interest within a 3-5 km range. Here are the details of the chosen scenario:

- **Urban Environment:** Central Business District (CBD), with high pedestrian density, landmarks, shopping districts, and cultural attractions.
- **Target Users:** Tourists
- **Acceptable Walking Distance:** 3-6 km; tourists are generally willing to walk longer distances to visit points of interest (Ewing & Handy, 2009).
- **Acceptable Slope Range:**

  Gentle slopes (0-3%) for smooth and comfortable walking.

Moderate slopes (3-5%) can be acceptable for tourists, especially when encountering landmarks and points of interest.

- **Priority Parameters:**
  - **Attractiveness:** High priority (45% weight), aesthetic areas.
  - **Safety:** Medium priority (25% weight)
  - **Comfort:** Medium priority (20% weight) to accommodate for potential inclines and uneven pavements.
  - **Accessibility:** Low priority (10% weight), as tourists may not be familiar or not interested with the efficient routes (e.g., shortest route).

- **Origin and Destination Pair:** For this use case we select the following origin and destination points as mapped in Figure 6.7:
  - **Origin:** Town Hall Railway Station
  - **Destination:** Sydney Opera House

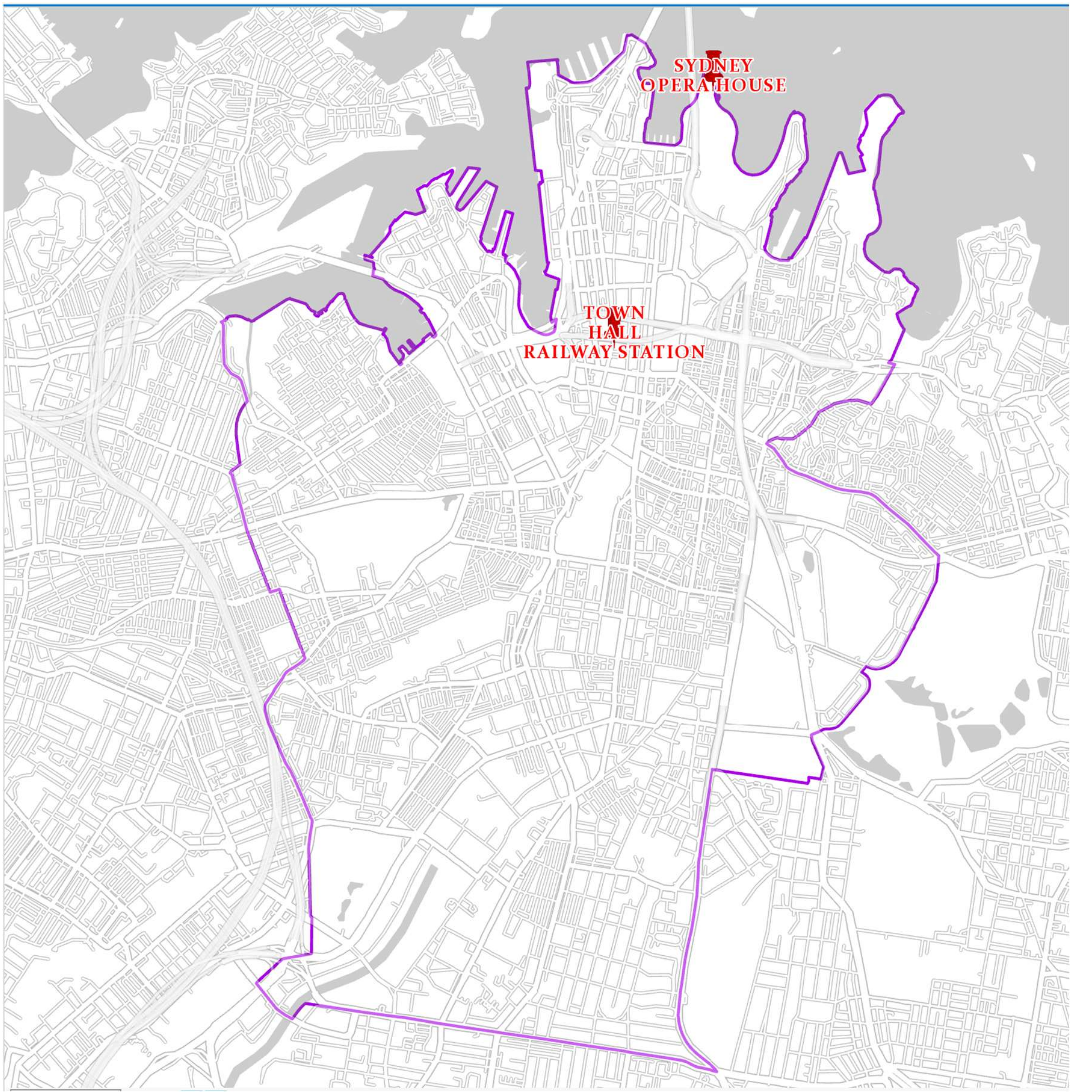


Figure 6.7 the location of origin and destination point of use case 1 in City of Sydney.

6.7 Use Case 1: Results of Algorithms Implementation based on Route Planning Scenarios

6.7.1 PB-MOACO Algorithm Implementation for Use Case 1

For Use Case 1, we implemented our customized PB-MOACO algorithm to optimize pedestrian route planning in Sydney's CBD, following the methodology detailed in Chapter 5. Before running the algorithm, we made several essential adjustments to ensure an effective and realistic optimization process. As we discussed at Section 6.1 to 6.4, first, we constructed a detailed (multi-dimensional) graph representation of the pedestrian network, where nodes represented critical decision points such as intersections, crosswalks, and mid-block waypoints and urban landuse characteristics, while edges incorporated essential attributes like safety, accessibility, and comfort. We, then, integrated hard constraints, such as maximum acceptable walking distance and slope limitations, to filter out infeasible routes and ensure practical solutions. The heuristic function also was designed to balance these factors, while the initial pheromone levels were adjusted based on preliminary analysis of the urban network, encouraging efficient exploration of diverse route options.

During the optimization process, we fine-tuned the pheromone parameters (α and β) to control the balance between heuristic guidance and pheromone influence, ensuring diverse yet practical route exploration. To maintain solution variety, we adapted the pheromone update mechanism to reinforce not only the shortest or safest routes but also those offering distinct trade-offs, such as scenic or comfier paths. Furthermore, we incorporated an adaptive stopping criterion, allowing the algorithm to dynamically terminate when the Pareto front stabilized while preserving route diversity.

After running 50 iterations (Table 6.2), we extracted the Pareto-optimal set, representing a spectrum of feasible routes. In the next stage, post-optimization techniques were applied to refine the selection further, resulting in the final optimal path tailored to tourist preferences.

6.7.1.1 Pareto Optimal Set

Based on a strict Pareto dominance check across all four objectives—Accessibility, Safety, Comfort, and Attractiveness—the PB-MOACO algorithm identified 11 routes as potential solutions. Among these, six routes (Path_17, Path_18, Path_19, Path_20, Path_26, and Path_30) are truly non-dominated solutions, meaning no other route in the set improves all four objectives simultaneously. These paths represent the most balanced trade-offs, ensuring efficient pedestrian route optimization under diverse urban conditions. Figure 6.8 present all six non-dominated solutions.

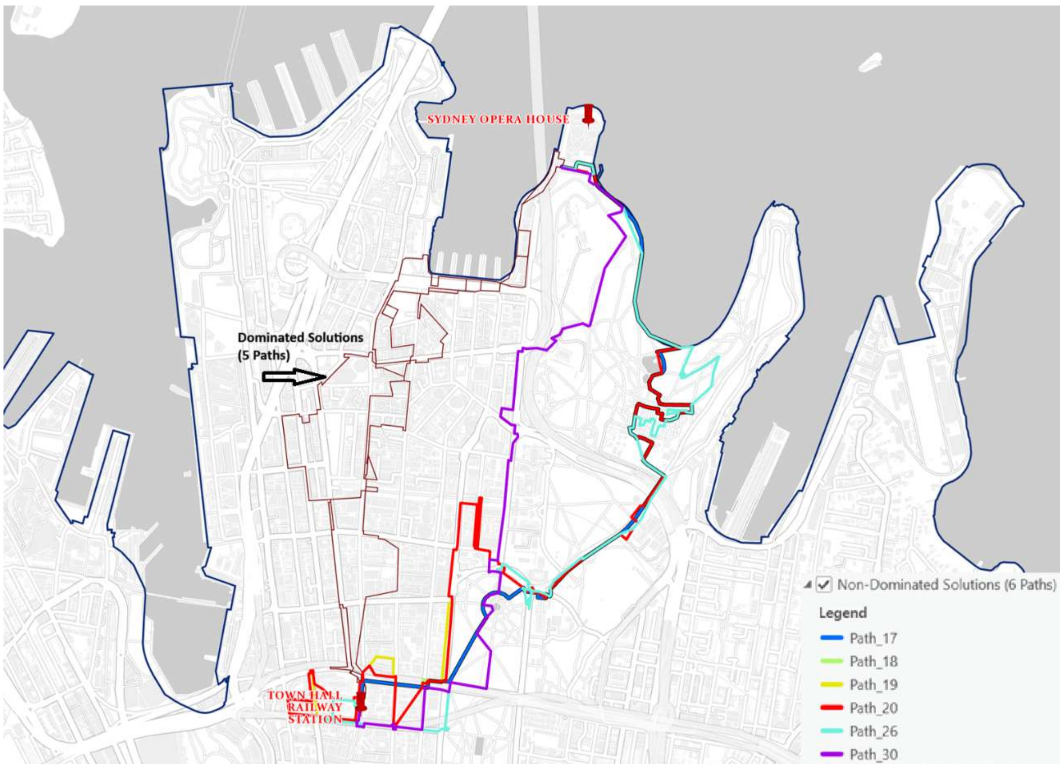


Figure 6.8 Identified PB-MOACO non-dominated solutions for use case 1

In addition, summary table xx capturing the key metrics and dominance insights for each Pareto-optimal path:

Table 6.2: key metrics and dominance insights for each Pareto-optimal path

	Pareto Optimal Set	Accessibility Score	Safety Score	Comfort Score	Attractiveness Score	Key Strengths
Non-Dominated Solutions	**Path_30**	312.84	363	960	721	**Best Accessibility**, strong Safety score
	Path_17	179.03	53	1620	1362	Strong Comfort/Attractiveness trade-off
	Path_18	180.96	40	1575	1362	Better Accessibility/Safety than Path_17
	Path_20	174.04	6	1530	1395	Higher Attractiveness than Path_19
	Path_19	183.62	13	1545	1338	Slightly better Accessibility than Path_20
	Path_26	211.95	88	1405	1322	Strong balance of Accessibility & Safety

This final Pareto set (Non-Dominated Solutions) allows decision-makers to prioritize routes based on the most critical objectives—whether Accessibility, Safety, Comfort, or Attractiveness.

However, the remaining five routes (Path_8, Path_10, Path_24, Path_38, and Path_39) are dominated solutions, meaning that at least one of the non-dominated routes outperforms them across all four objectives. While these dominated paths remain part of the set for reference (comparison only), they are suboptimal compared to the strictly non-dominated routes. This refined selection process ensures that only the most efficient and well-balanced pedestrian routes are offered by the PB-MOACO algorithm, allowing decision-makers to prioritize based on specific urban planning needs. Table 6.3 provide key metrics for each dominated path.

Table 6.3: key metrics of each dominated path

Dominated Solutions	Accessibility	Safety	Comfort	Attractiveness
Path_8	312.27	13	1145	766
Path_10	311.63	0	1165	775
Path_24	296.80	-127	940	805
Path_38	293.82	-50	1060	687
Path_39	288.65	-41	1105	712

6.7.1.2 Post Optimisation for Final Path Selection

After identifying the Pareto-optimal set, a post-optimisation process is conducted to determine the most suitable pedestrian path based on the given priorities for Accessibility, Safety, Comfort, and Attractiveness. This step ensures a data-driven final selection by integrating normalized objective functions and a weighted sum approach.

Step 1: Normalization of Objective Functions

To fairly compare all objectives, each criterion is normalized within a [0,1] range. The best-performing value in each objective receives 1, while the worst receives 0. The normalized values for each path are presented in the table 6.4, ensuring a standardized comparison framework.

Table 6.4: Normalized values of Objective Functions- step 1

		Post – Optimisation			
		Step 1: Define the Normalized Objective Functions			
	Pareto Optimal Set	Accessibility	Safety	Comfort	Attractiveness
Non-Dominated Solutions	Path_30	1.00	1.00	0.00	0.00
	Path_17	0.04	0.13	1.00	0.95
	Path_18	0.05	0.10	0.93	0.95
	Path_20	0.00	0.00	0.86	1.00
	Path_19	0.07	0.02	0.89	0.92
	Path_26	0.27	0.23	0.67	0.89
Min Original Value		174.04	6.00	960.00	721.00
Max Original Value		312.84	363.00	1620.00	1395.00

Step 2: Weighted Sum of Objectives

To account for different stakeholder preferences, a weighted sum approach is applied. The following weights are assigned based on priority considerations (Table 6. 5):

- Accessibility: 10% (Lower priority)

- Safety: 25% (Moderate priority)
- Comfort: 20% (Moderate priority)
- Attractiveness: 45% (Highest priority)

Each path's score is calculated as:

$$Final\ Score = (0.1 \times Normalized\ Accessibility) + (0.25 \times Normalized\ Safety) + (0.2 \times Normalized\ Comfort) + (0.45 \times Normalized\ Attractiveness)$$

The computed scores indicate how well each path aligns with the defined priorities.

Table 6.5: Normalized values of Objective Functions- step 2

		Post – Optimisation				
		Step 2: Weighted Sum of Objectives				
	Pareto Optimal Set	Accessibility (10%)	Safety (25%)	Comfort (20%)	Attractiveness (45%)	Sum
Non-Dominated Solutions	Path_30	0.1	0.25	0.00	0.00	0.35
	Path_17	0.0036	0.03	0.20	0.43	**0.66**
	Path_18	0.0050	0.02	0.19	0.43	0.64
	Path_20	0.0000	0.00	0.17	0.45	0.62
	Path_19	0.0069	0.00	0.18	0.41	0.60
	Path_26	0.0273	0.06	0.13	0.40	0.62
Step 3: Selection of Final Path						Max Value:
Best Path based on user Preferences			Path_17			0.66

Step 3: Final Path Selection

Based on the weighted sum, **Path_17 achieves the highest score (0.66), making it the final recommended path (**Figure 6.9). Path_18 and Path_26 follow closely, indicating strong alternatives. Path_30, despite excelling in Accessibility and Safety, ranks lowest due to its poor Comfort and Attractiveness.

This post-optimisation process refines the Pareto-optimal set, ensuring the final selection best aligns with urban planning objectives and pedestrian preferences.

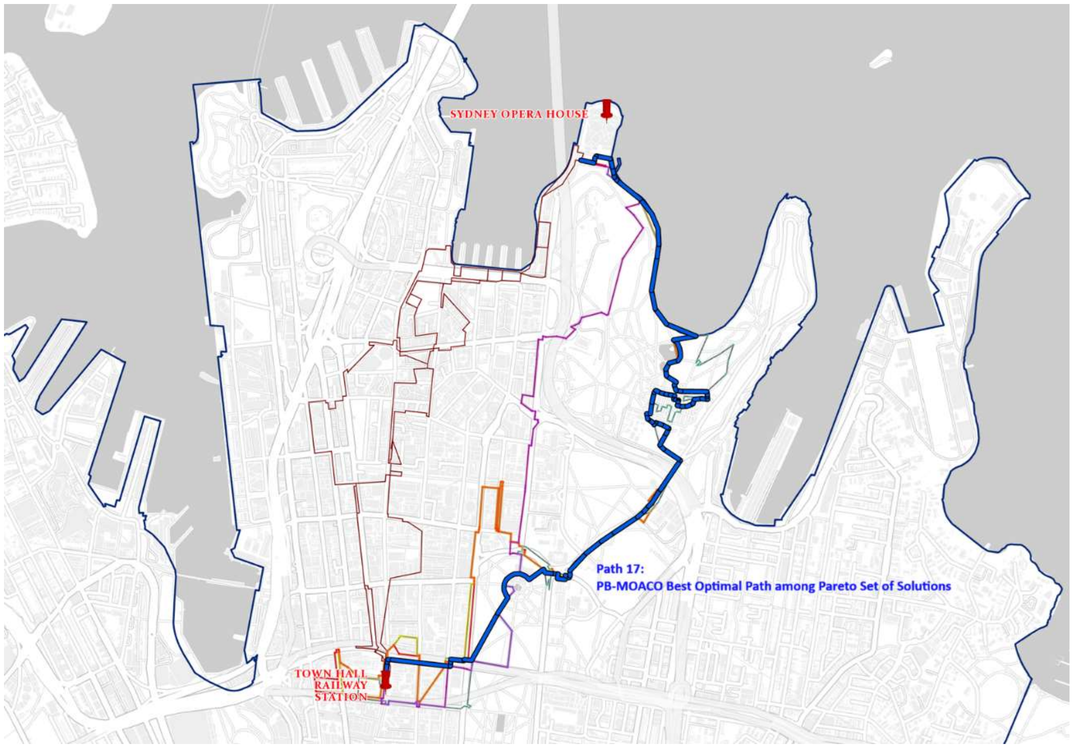


Figure 6.9: PB-MOACO Best Path Among Pareto Set of Solutions

Table 6.6 summarizes the key aspects of the route derived using PB-MOACO algorithm.

Table 6.6: Key aspects of the route derived using PB-MOACO algorithm

Parameters	Score	Description
Accessibility	3035.78 m	Path length, making it accessible for pedestrians.
Comfort	0.85	Indicates a high level of comfort with manageable slopes and terrain.
Safety	0.13	Moderate safety, especially for tourists at night.
Attractiveness	0.95	A mix of practical amenities, scenic views, and cultural attractions along the route.

6.7.2 MOACO-WA Algorithm:

For Use Case 1, we implemented the MOACO-WA algorithm to optimize pedestrian route selection in the Sydney CBD, considering safety, comfort, accessibility, and attractiveness. The process began by defining the pedestrian network as a weighted graph, where nodes represented intersections and key locations, and edges carried attributes influencing pedestrian movement. Initial pheromone levels were set uniformly, and user preference weights ensured a balanced influence of each objective. A key component was the heuristic calculation, which determined edge desirability based on a weighted aggregation of normalized scores: safety (street visibility), comfort (slope and pedestrian-friendly features), accessibility (inverse distance), and attractiveness (urban land use). The heuristic function $\eta(i,j)$ integrated these scores, ensuring that edges with higher values were more likely to be selected. This function played a crucial role in the path construction phase, guiding virtual ants as they traversed the network by selecting edges probabilistically based on pheromone strength and heuristic values.

During each iteration, ants built complete paths from a start to an end node, recording their route costs using an aggregated cost function, where higher values of safety, comfort, accessibility, and attractiveness resulted in a lower cost, favoring desirable paths. After all ants completed their paths, pheromone levels were updated—evaporating uniformly to avoid premature convergence while reinforcing high-quality paths based on their inverse cost. The algorithm also adapted parameters dynamically, periodically resetting pheromones or adjusting α, β, and evaporation rates to enhance exploration. Finally, after multiple iterations, all generated paths were evaluated, and the route with the lowest aggregated cost was selected as the optimal path, ensuring a well-balanced pedestrian experience based on multi-objective criteria and user-defined preferences. Figure 6.10 present the final single Path generated by MOACO-WA Algorithm.

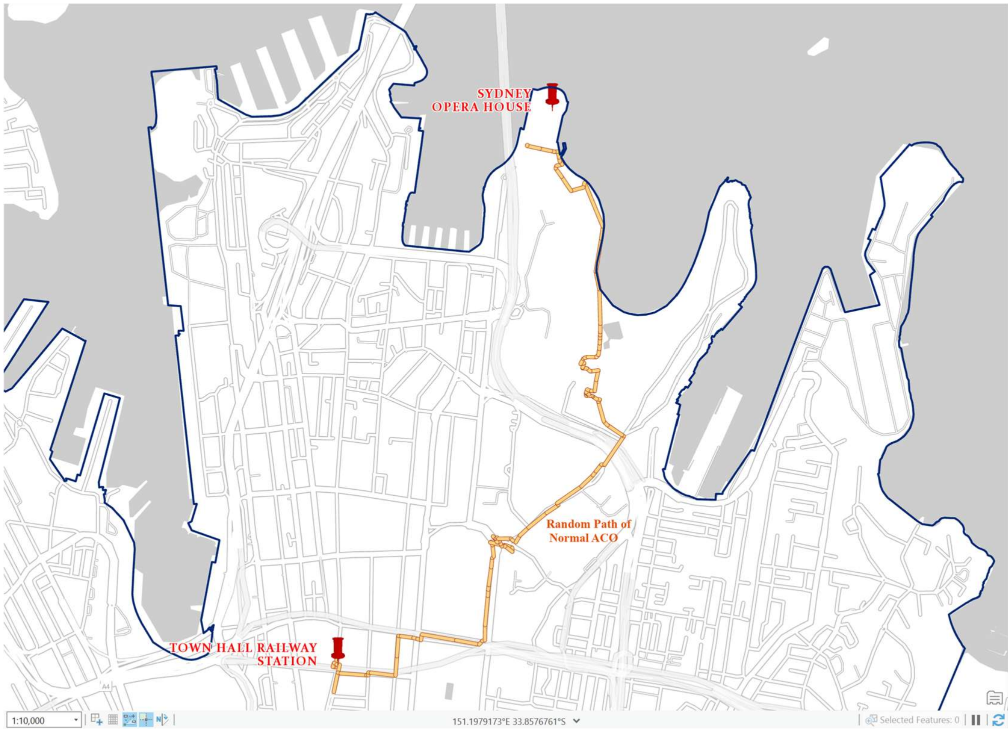


Figure 6.10 Path of MOACO-WA Algorithm

Figure 6.9 illustrates the outcome of applying MOACO-WA's algorithm to derive a walking route between origin and destination points. The orange line represents the selected pathway, optimized primarily for the final single path based on aggragated cost function and weights of user preferences. Table 6.7 summarizes the key aspects of the route derived using MOACO-WA algorithm.

Table 6.7: Key aspects of the route derived using MOACO-WA algorithm

Parameters	Score	Description
Accessibility	3743.27 m	Path length, making it accessible but longer than desired for some pedestrians.
Comfort	0.7	Indicates a moderately high comfort level, though some areas may have challenging terrain.
Safety	0.15	Low safety score, requiring pedestrians to exercise caution in certain areas.
Attractiveness	0.83	High attractiveness due to strong emphasis on recreation, culture, and scenic point of interests.

6.7.3 Dijkstra's Algorithm:

For Use Case 1, we implemented Dijkstra's algorithm to determine the shortest path for pedestrians navigating Sydney CBD. The spatial network was represented as a graph where intersections and waypoints served as nodes, and sidewalks or pathways formed the edges, each assigned a default traversal cost based solely on distance. During initialization, we set the starting node's distance to zero, assigned an infinite distance to all other nodes, and maintained a priority queue for efficient traversal. The algorithm iteratively selected the node with the smallest distance, updated its neighbors if a shorter path was found, and continued until reaching the destination. Once the destination node was extracted from the queue, the shortest path was reconstructed through backtracking. The implementation followed the standard Dijkstra process without additional modifications, ensuring a direct comparison with our proposed PB-MOACO algorithm. Figure 6.11 illustrates shortest path calculation using Dijkstra's algorithm.

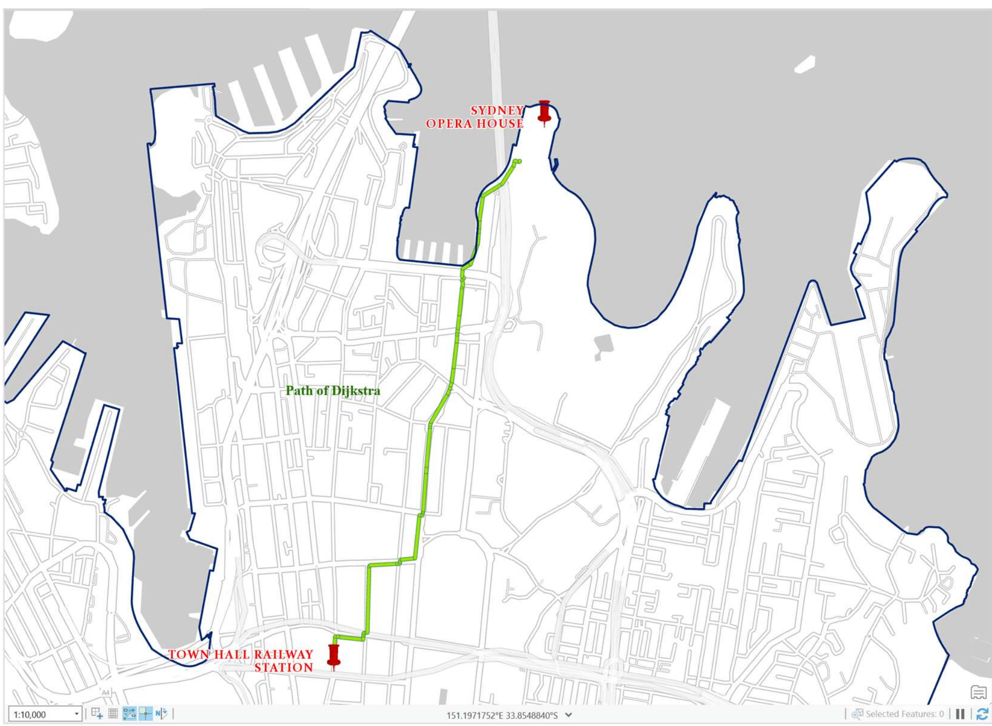


Figure 6.11 shortest path calculation using Dijkstra's algorithm.

Figure 6.11 illustrates the outcome of applying Dijkstra's algorithm to derive a walking route between origin and destination points. The green line represents the selected pathway, optimized primarily for the shortest distance. Table 6.8 summarizes the key aspects of the route derived using Dijkstra's algorithm.

Table 6.8: Key aspects of the route derived using Dijkstra's algorithm

Parameters	Score	Description
Accessibility	2209.75 m	Path length, making it accessible for pedestrians.
Comfort	0.79	Indicates a high level of comfort with manageable slopes and terrain.
Safety	0.47	Moderate safety, especially for tourists at night.
Attractiveness	0.72	A mix of practical amenities, scenic views, and cultural attractions along the route.

6.8 Use Case 1: Comparison Results Analysis of PB-MOACO vs. MOACO-WA vs. Dijkstra

In this comparative analysis of pedestrian route planning algorithms, PB-MOACO, MOACO-WA, and Dijkstra's approach were evaluated based on four key criteria: safety, comfort, accessibility, and attractiveness. Table 6.9 provides a summary of the normalized scores for each parameter, allowing for a direct comparison across the three algorithms.

Dijkstra's algorithm excels in safety (0.47) and provides the shortest route (2209.75m), making it the most accessible option. However, it falls behind in attractiveness (0.72), as it prioritizes efficiency over scenic value, resulting in less engaging routes for tourists. On the other hand, MOACO-WA achieves a higher attractiveness score (0.83) by incorporating various urban land uses and scenic elements along the route, but at the expense of safety (0.15) and accessibility (3743.27m). PB-MOACO demonstrates the best overall balance, optimizing for attractiveness (0.95) and comfort (0.85) while maintaining a reasonable accessibility score (3035.78m). However, its low safety score (0.13) suggests that the algorithm prioritizes aesthetic appeal and user experience over security considerations.

- **Performance Comparison of Algorithms**

Table 6.9 presents a side-by-side comparison of the three algorithms:

Algorithm	Safety Score (0 - 1)	Comfort Score (0 - 1)	Accessibility (Length/m)	Attractiveness Score (0 - 1)
Dijkstra	0.47	0.79	2209.75	0.72
MOACO-WA	0.15	0.7	3743.27	0.83
PB-MOACO	0.13	0.85	3035.78	0.95

- **Which Algorithm Performed Best?**

As shown in Table 6.6, PB-MOACO is the best choice for tourists seeking scenic and comfortable walking routes, achieving the highest attractiveness (0.95) and comfort (0.85). Despite its low safety score (0.13), its prioritization of aesthetic areas aligns well with user preferences that emphasize attractiveness. MOACO-WA offers a balanced alternative, achieving a strong attractiveness score (0.83) while providing moderate comfort (0.7). However, it also has a relatively low safety score (0.15), making it less ideal for risk-averse pedestrians.

Dijkstra's algorithm remains the safest (0.47) and most accessible option (2209.75m) but ranks the lowest in attractiveness (0.72) and comfort (0.79). While it is the best choice for users prioritizing safety and efficiency, it is less suitable for tourists seeking an engaging and visually appealing experience.

- **Figures and Visual Comparisons**

Figure 6.12 illustrates the generated paths for each algorithm, highlighting differences in routing choices between PB-MOACO, MOACO-WA, and Dijkstra's method.

Figure 6.12 map of the three generated path between origin and destinations points.

Figure 6.13 provides a safety comparison, where Dijkstra performs best, while PB-MOACO and MOACO-WA score significantly lower.

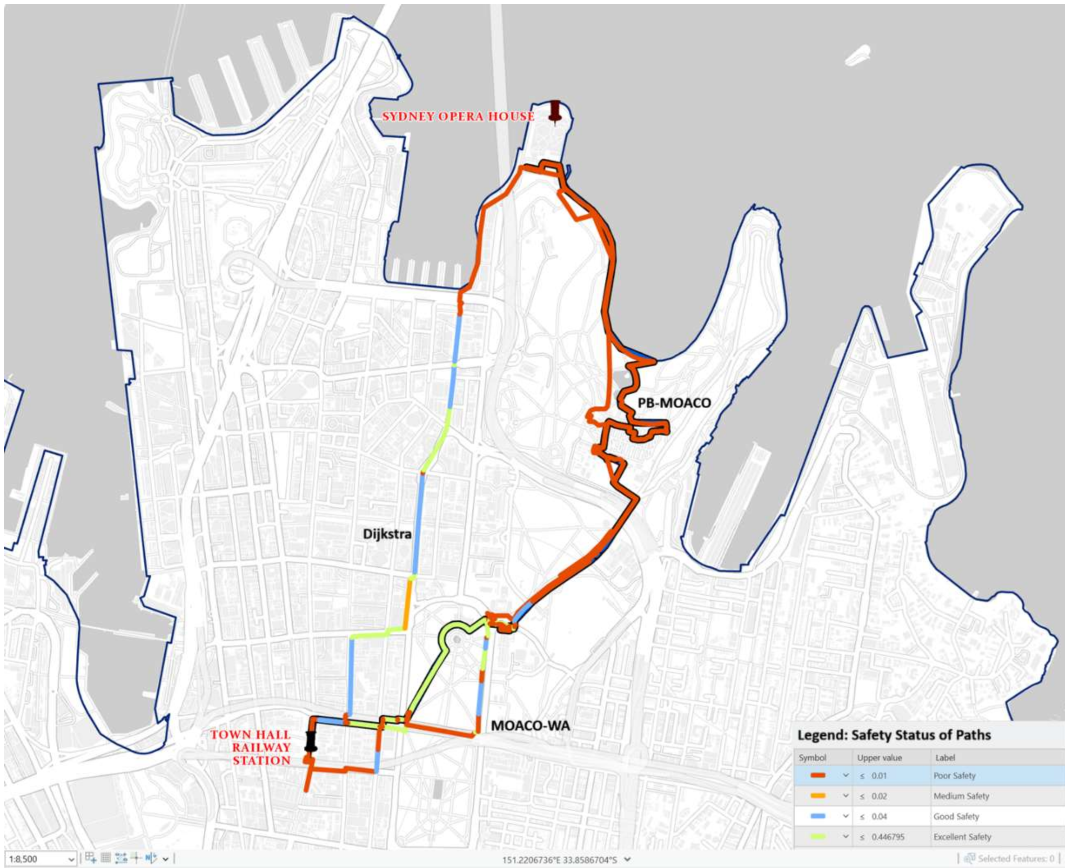


Figure 6.13 Safety comparison of three different routing approaches —PB-MOACO, MOACO-WA, Dijkstra

Figure 6.14 visualizes comfort differences, showcasing how PB-MOACO optimizes pedestrian experience, whereas MOACO-WA and Dijkstra have moderate variations in terrain difficulty.

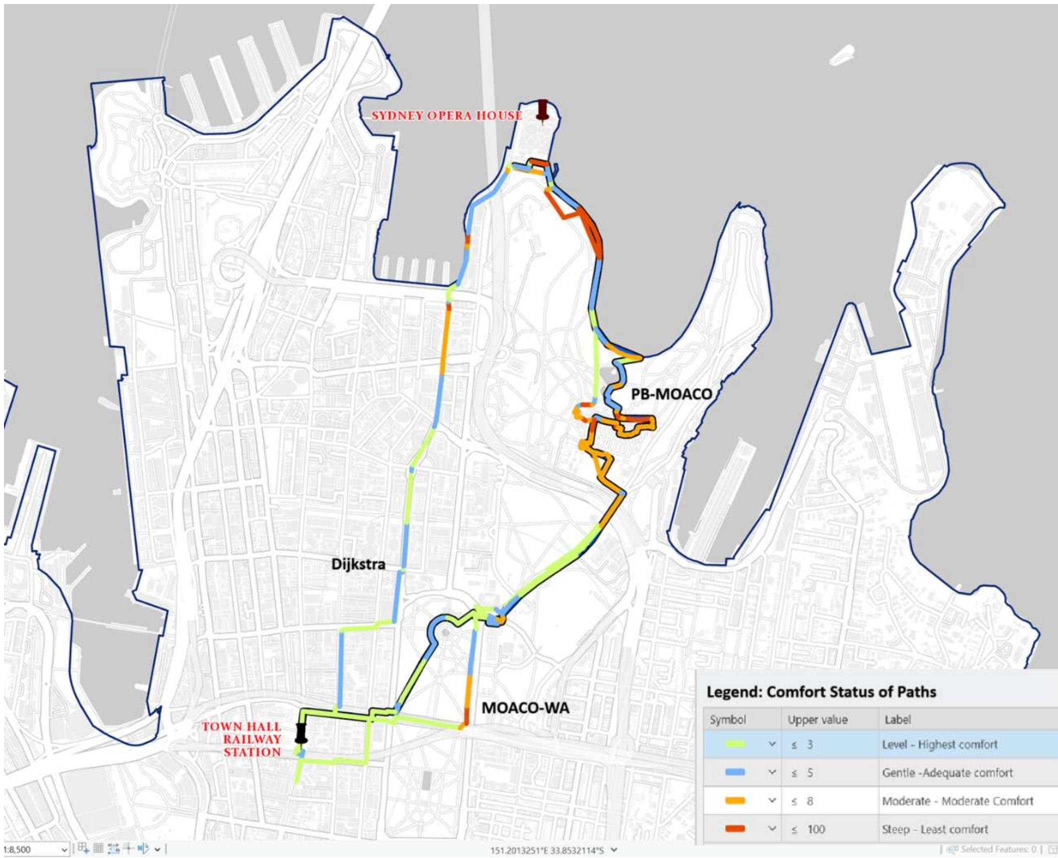


Figure 6.14 Comfort comparison of three different routing approaches — MOACO-WA, PB-MOACO, and Dijkstra's algorithm

Figure 6.15 compares urban land use distributions across the three algorithms, demonstrating how PB-MOACO and MOACO-WA emphasize scenic and cultural POIs more effectively than Dijkstra.

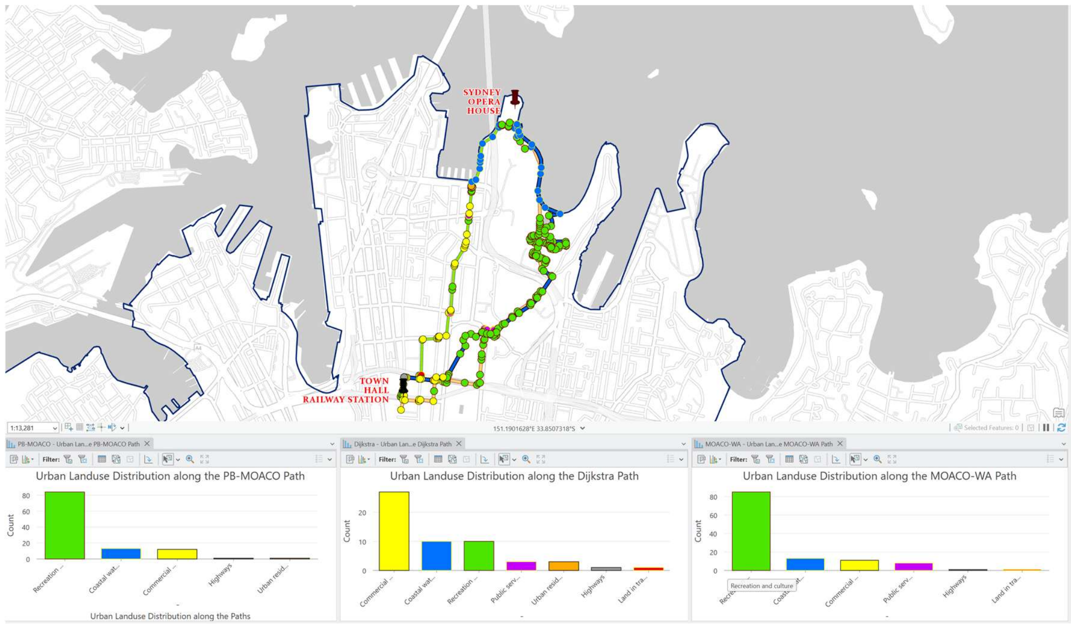


Figure 6.15 Comparison of urban land use distributions for three different routing approaches — MOACO-WA, PB-MOACO, and Dijkstra's algorithm.

Conclusion

PB-MOACO emerges as the most effective algorithm for pedestrian route planning in tourist contexts, offering the highest attractiveness and comfort. MOACO-WA provides a viable alternative with a balance of attractiveness and accessibility, while Dijkstra remains the best option for users prioritizing safety and efficiency. However, all three algorithms could benefit from further refinements to better balance safety, comfort, and accessibility while maintaining scenic appeal.

6.9 Use Case 2: Commuters in Inner Suburb

In this use case, the emphasis is on commuters traveling within the inner suburban areas of Sydney. The goal is to evaluate the algorithm's efficiency in delivering safe, direct, and comfortable routes between residential neighbourhoods and key transportation hubs or workplaces. For urban commuters, research indicates that route selection typically emphasizes efficiency and safety over aesthetics and comfort. Based on these insights, a common set of normalized weights (on a 0–1 scale) for the four categories might be:

- **Urban Environment:** Inner Suburb, characterized by residential areas, local businesses, and transit hubs.
- **Pedestrian Type:** Commuter
- **Acceptable Walking Distance:** 1-3 km; commuters prefer shorter, efficient routes for everyday travel.
- **Priority Parameters:**
  - **Accessibility:** High priority (40% weight) for efficient routes to work or transit hubs.
  - **Safety:** Very high priority (30% weight) for safety in daily travel.
  - **Comfort:** Medium priority (15% weight), with preference for gentle slopes and clear pathways.
  - **Attractiveness:** Medium priority (15% weight); commuters prioritize efficiency over scenery.

This allocation reflects that commuters generally prioritize shorter, more direct routes (Accessibility) and safe environments (Safety), while aspects such as comfort and attractiveness, though important, tend to be secondary. Studies by (Handy et al., 2002) and (Ewing & Handy, 2009) support these preferences by showing that route choices among commuters are primarily driven by efficiency and perceived safety.

- **Origin and Destination Pair:** For this use case we select the following origin and destination points (Figure 6.16).:

  Origin: GREEN SQUARE COMMUNITY HALL **OSM ID: 6771807309**

  Destination: WATERLOO RAILWAY STATION **OSM ID: 11118810847**

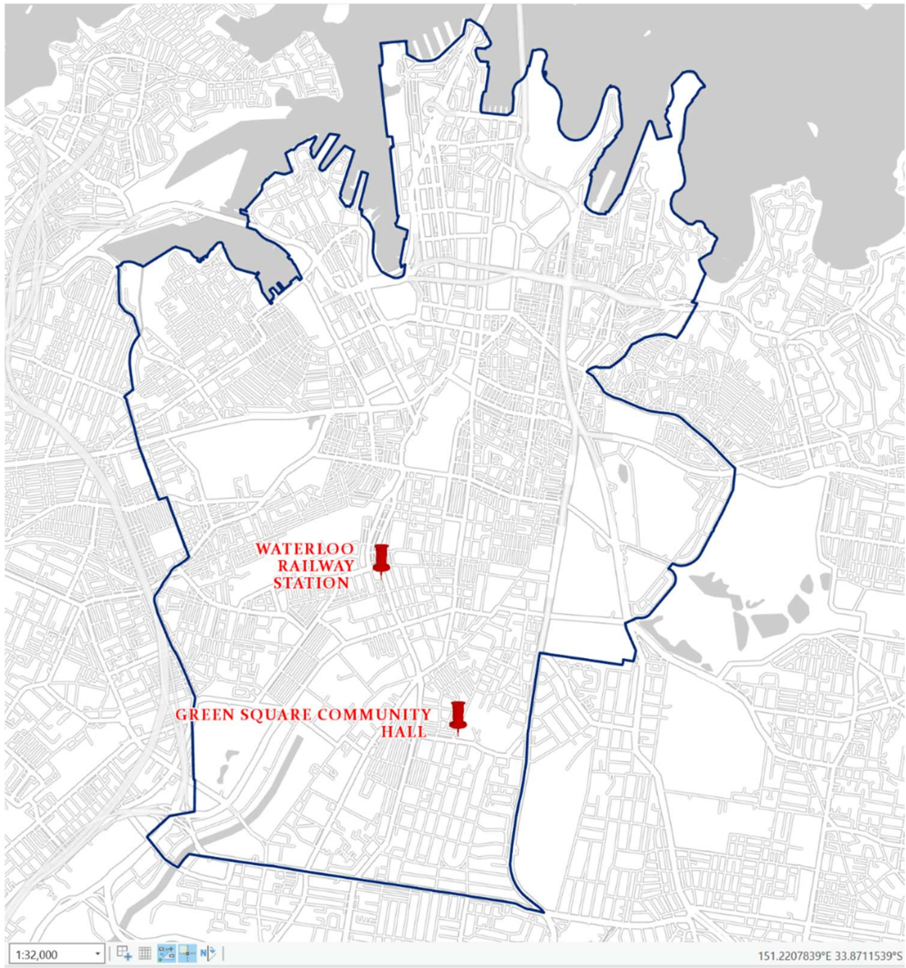


Figure 6.16 Location of origin and destination points in use case 2

6.10 Use Case 2: Results of Algorithms Implementation based on Route Planning Scenarios

6.10.1 PB-MOACO Algorithm Implementation for Use Case 2

As we discussed for Use Case 1 at Section 6.7.1, for Use Case 2 also we implemented our customized PB-MOACO algorithm to optimize pedestrian route planning in Sydney's CBD, following the methodology detailed in Chapter 5.

After running 50 iterations (Table 6.10), we extracted the Pareto-optimal set (Figure 6.17), representing a spectrum of feasible routes. In the next stage, post-optimization techniques were applied to refine the selection further, resulting in the final optimal path tailored to tourist preferences.

6.10.1.1 Pareto Optimal Set

Based on a strict Pareto dominance check across all four objectives—Accessibility, Safety, Comfort, and Attractiveness—the PB-MOACO algorithm identified **8 routes** as pareto optimal solutions (Path_35, Path_19, Path_31, Path_33, Path_5, Path_17, Path_47, and Path_24) are truly non-dominated solutions, meaning no other route in the set improves all four objectives simultaneously. These paths represent the most balanced trade-offs, ensuring efficient pedestrian route optimization under diverse urban conditions. Figure 6.17 present all eight non-dominated solutions.

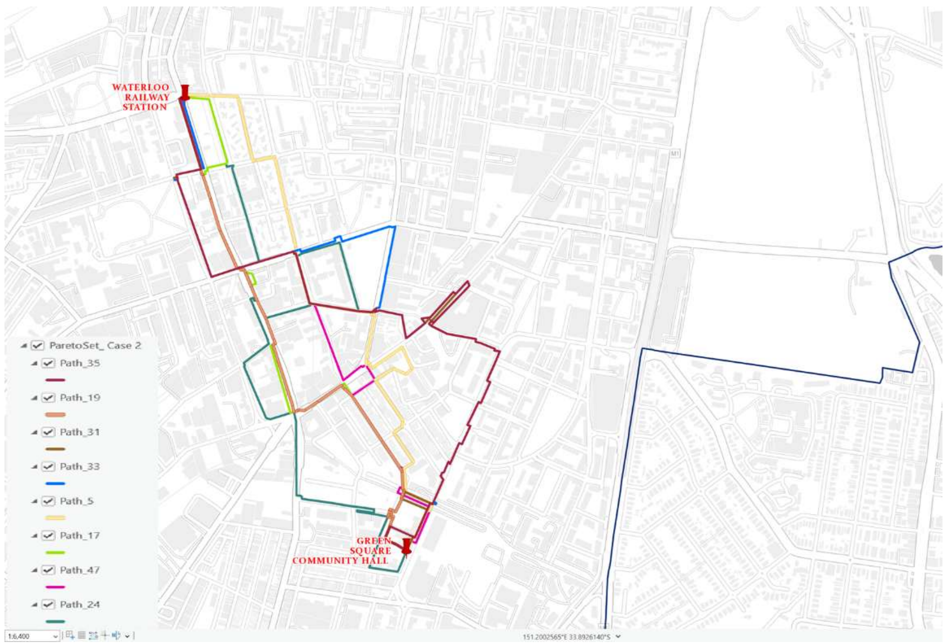


Figure 6.17: Identified PB-MOACO non-dominated solutions for use case 2

In addition, table 6.10 capturing the key metrics and dominance insights for each Pareto-optimal path:

Table 6.10: key metrics and dominance insights for each Pareto-optimal path

	Pareto Optimal Set	Accessibility Score	Safety Score	Comfort Score	Attractiveness Score
Non-Dominated Solutions	**Path_35**	324.29	194	1230	650
	Path_19	517.88	-69	875	378
	Path_31	325.94	142	1225	642
	Path_33	334.77	119	1195	650

	Path_5	430.46	183	1200	450
	Path_17	475.84	-16	955	407
	Path_47	482.06	92	645	312
	Path_24	331.05	163	880	389
Min		324.29	-69	645	312.00
Max		517.88	194	1230	650.00

➢ **Key Strengths**

- **Path_35:** Dominates in Safety (194), Comfort (1230), and Attractiveness (650). While its Accessibility (324.29) is lower, no other path surpasses it in all three other parameters.
- **Path_19:** Highest Accessibility (517.88). Though weaker in other parameters, no path has higher Accessibility without sacrificing Safety, Comfort, or Attractiveness further.
- **Path_31:** High Comfort (1225) and Attractiveness (642). Not dominated by Path_35 due to better Accessibility (325.94 vs. 324.29) but lower Safety.
- **Path_33:** Tied highest Attractiveness (650) and high Comfort (1195). Better Accessibility (334.77) than Path_35 but lower Safety.
- **Path_5:** High Comfort (1200) with balanced Accessibility (430.46). Not dominated due to its strong Safety, Comfort and reasonable Accessibility.
- **Path_17:** Best Comfort (955) and Attractiveness (407) among high-Accessibility paths (475.84). Uniquely balances Accessibility with Comfort/Attractiveness.
- **Path_47:** High Safety (92) within high-Accessibility paths (482.06). No other high-Accessibility path offers better Safety without trade-offs.
- **Path_24:** Balances Safety (163), Comfort (880), and Attractiveness (389). Not dominated by other Safety-focused paths.

This final Pareto set (Non-Dominated Solutions) allows decision-makers to prioritize routes based on the most critical objectives—whether Accessibility, Safety, Comfort, or Attractiveness.

6.10.1.2 Post Optimisation for Final Path Selection

After identifying the Pareto-optimal set, a post-optimisation process is conducted to determine the most suitable pedestrian path based on the given priorities for Accessibility, Safety, Comfort, and Attractiveness. This step ensures a data-driven final selection by integrating normalized objective functions and a weighted sum approach.

Step 1: Normalization of Objective Functions

To fairly compare all objectives, each criterion is normalized within a [0,1] range. The best-performing value in each objective receives 1, while the worst receives 0. The normalized values for each path are presented in the table 6.11, ensuring a standardized comparison framework.

Table 6.11: Normalized values of Objective Functions- Step1

		Post – Optimisation			
		Step 1: Define the Normalized Objective Functions			
	Pareto Optimal Set	Accessibility	Safety	Comfort	Attractiveness
Non-Dominated Solutions	Path_35	0.00	1.00	1.00	1.00
	Path_19	1.00	0.00	0.39	0.20
	Path_31	0.01	0.80	0.99	0.98
	Path_33	0.05	0.71	0.94	1.00
	Path_5	0.55	0.96	0.95	0.41
	Path_17	0.78	0.20	0.53	0.28
	Path_47	0.81	0.61	0.00	0.00
	Path_24	0.03	0.88	0.40	0.23

Step 2: Weighted Sum of Objectives

To account for different stakeholder preferences, a weighted sum approach is applied. The following weights are assigned based on priority considerations (Table 6.12):

- **Accessibility:** 40% (Highest priority)
- **Safety:** 30% (Moderate priority)
- **Comfort:** 15% (Lower priority)
- **Attractiveness:** 15% (Lower priority)

Each path's score is calculated as:

$$\begin{aligned} Final\ Score = \ & (0.1 \times Normalized\ Accessibility) + (0.25 \times Normalized\ Safety) \\ & + (0.2 \times Normalized\ Comfort) + (0.45 \times Normalized\ Attractiveness) \end{aligned}$$

The computed scores indicate how well each path aligns with the defined priorities.

Table 6.12: Normalized values of Objective Functions- step 2

		Post – Optimisation				
		Step 2: Weighted Sum of Objectives				
	Pareto Optimal Set	Accessibility (10%)	Safety (25%)	Comfort (20%)	Attractiveness (45%)	Sum
Non-Dominated Solutions	**Path_35**	0.00	0.30	0.15	0.15	0.60
	Path_19	0.40	0.00	0.06	0.03	0.49
	Path_31	0.00	0.24	0.15	0.15	0.54
	Path_33	0.02	0.21	0.14	0.15	0.53
	Path_5	0.22	0.29	0.14	0.06	0.71
	Path_17	0.31	0.06	0.08	0.04	0.50
	Path_47	0.33	0.18	0.00	0.00	0.51
	Path_24	0.01	0.26	0.06	0.03	0.37
Step 3: Selection of Final Path						**Max Value:**
Best Path based on user Preferences			Path_5			**0.71**

Step 3: Final Path Selection

Based on the weighted sum of objectives, **Path_5 achieves the highest score (0.71), making it the final recommended path** (Figure 6.18). This selection balances Accessibility (0.22), Safety (0.29), Comfort (0.14), and Attractiveness (0.06), ensuring an optimal trade-off between efficiency and pedestrian experience.

Among the strong alternatives, Path_35 (0.60) and Path_31 (0.54) demonstrate competitive performance, particularly in safety and comfort, making them viable choices in scenarios prioritizing these factors. However, Path_19, despite excelling in Accessibility (0.40), ranks lower due to its poor Safety (0.00) and Comfort (0.06), highlighting the necessity of a balanced approach in pedestrian route planning.

This post-optimization process refines the Pareto-optimal set, ensuring that the final selection aligns with urban planning goals and pedestrian preferences. By integrating multi-objective evaluation, this approach enhances walkability, safety, and overall user satisfaction, contributing to more sustainable and pedestrian-friendly urban environments.

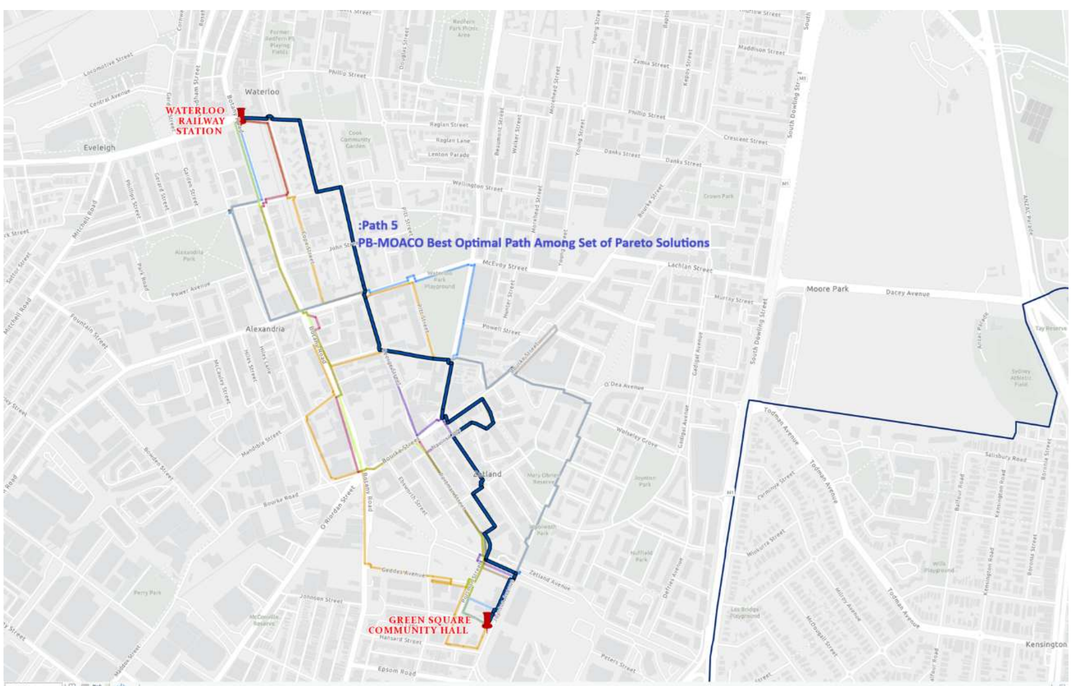


Figure 6.18: PB-MOACO Best Path Among Pareto Set of Solutions

Table 13 summarizes the key aspects of the route derived using PB-MOACO algorithm.

Table 6.13: Key aspects of the route derived using PB-MOACO algorithm

Parameters	**Score**	**Description**
Accessibility	2323.1 m	A well-balanced path length, offering reasonable accessibility.
Comfort	0.94	High comfort level, ensuring a smooth and enjoyable walking experience.
Safety	0.31	Improved safety compared to MOACO-WA but still lower than Dijkstra's approach.
Attractiveness	0.67	The most attractive route among the three, incorporating aesthetic and scenic elements.

6.10.2 MOACO-WA Algorithm:

For Use Case 2, we also implemented the MOACO-WA algorithm to optimize pedestrian route selection in the Sydney CBD, considering safety, comfort, accessibility, and attractiveness. The optimisation process details explained at Section 5.6.1. As also discussed at Section 6.7.2 the same configuration and adjustment also applied for this use case. Figure 6.19 illustrates the outcome of applying MOACO-WA's algorithm to derive a walking route between origin and destination points. The orange line represents the selected pathway, optimized primarily for the final single path based on aggregated cost function and weights of user preferences. Table 6.14 summarizes the key aspects of the route derived using MOACO-WA algorithm.

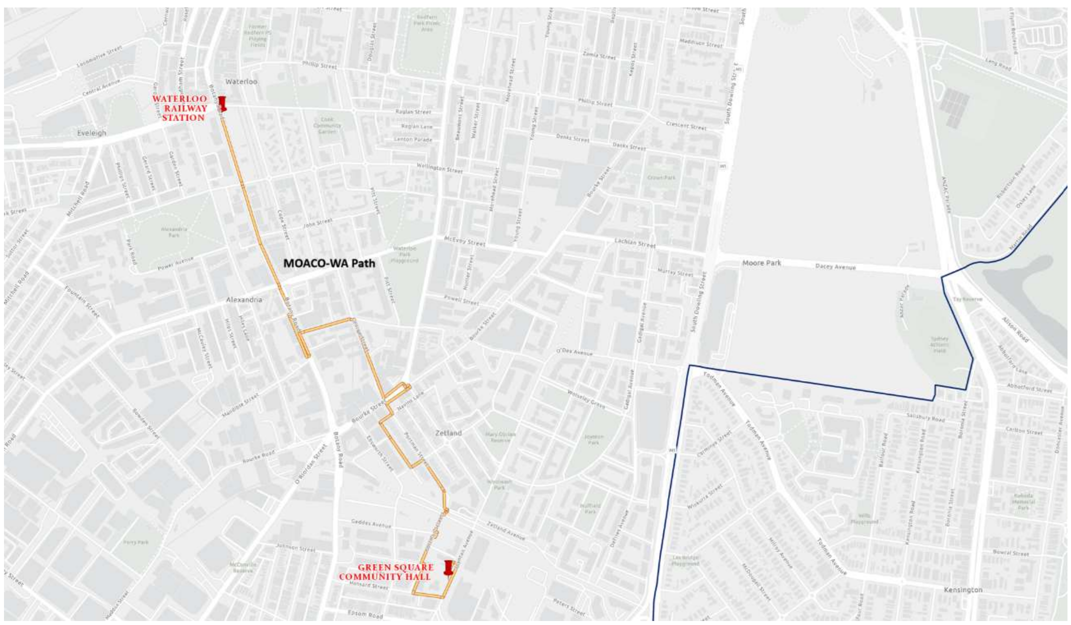


Figure 6.19 Path of MOACO-WA Algorithm

Table 6.14: Key aspects of the route derived using MOACO-WA algorithm

Parameters	Score	Description
Accessibility	2535.46 m	The path length is moderate but longer than the shortest available route.
Comfort	0.94	High comfort level, ensuring a smooth and pedestrian-friendly experience.
Safety	0.21	Improved safety compared to other approaches but still requires caution.

Attractiveness	0.62	Moderate attractiveness, balancing efficiency with scenic elements.

6.7.4 Dijkstra's Algorithm:

For Use Case 2, we implemented Dijkstra's algorithm to determine the shortest path for pedestrians navigating Sydney CBD. The spatial network was represented as a graph where intersections and waypoints served as nodes, and sidewalks or pathways formed the edges, each assigned a default traversal cost based solely on distance. During initialization, we set the starting node's distance to zero, assigned an infinite distance to all other nodes, and maintained a priority queue for efficient traversal. The algorithm iteratively selected the node with the smallest distance, updated its neighbors if a shorter path was found, and continued until reaching the destination. Once the destination node was extracted from the queue, the shortest path was reconstructed through backtracking. The implementation followed the standard Dijkstra process without additional modifications, ensuring a direct comparison with our proposed PB-MOACO algorithm. Figure 6.20 illustrates shortest path calculation using Dijkstra's algorithm. Figure 6.20 illustrates the outcome of applying Dijkstra's algorithm to derive a walking route between origin and destination points. The green line represents the selected pathway, optimized primarily for the shortest distance.

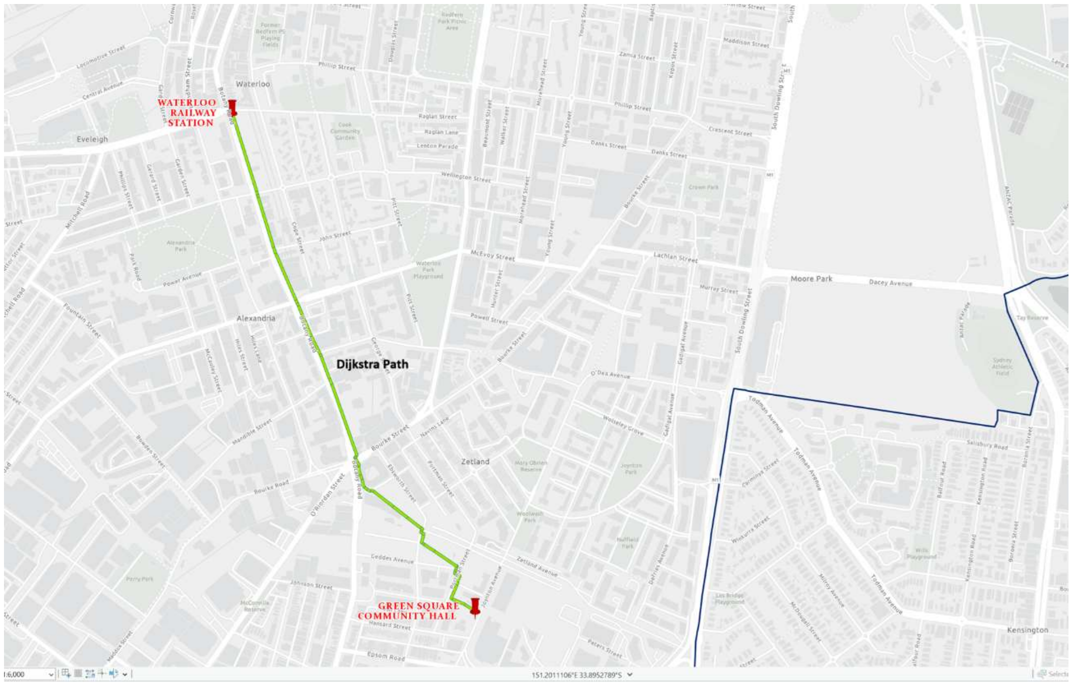


Figure 6.20 shortest path calculation using Dijkstra's algorithm.

Table 6.15 summarizes the key aspects of the route derived using Dijkstra's algorithm.

Table 6.15: Key aspects of the route derived using Dijkstra's algorithm

Parameters	Score	Description
Accessibility	1663.90 m	Shortest path, making it the most efficient in terms of distance.
Comfort	0.86	High comfort level, ensuring a relatively smooth walking experience.
Safety	0.11	Lowest safety score, potentially exposing pedestrians to unsafe conditions especially at night.
Attractiveness	0.54	Least attractive route, prioritizing efficiency over scenic or cultural value.

6.11 Use Case 2: Comparison Results Analysis of PB-MOACO vs. MOACO-WA vs. Dijkstra

➢ **Performance Comparison of Algorithms**

In this comparative analysis, PB-MOACO, MOACO-WA, and Dijkstra's algorithm were evaluated based on four key criteria: safety, comfort, accessibility, and attractiveness. Table 6.16 summarizes the normalized scores for each parameter, facilitating a direct comparison across the three algorithms.

Table 6.16 Summary Comparison of Pedestrian Route Planning Algorithms

Algorithm	**Safety Score (0 - 1)**	**Comfort Score (0 - 1)**	**Accessibility (Length/m)**	**Attractiveness Score (0 - 1)**
Dijkstra	0.11	0.86	1663.90	0.54
MOACO-WA	0.21	0.94	2535.46	0.62
PB-MOACO	0.31	0.94	2,323.1	0.67

Dijkstra's algorithm provides the shortest and most accessible route (1663.90m) but ranks the lowest in attractiveness (0.54). Its safety score (0.11) is also the lowest, indicating that the shortest route does not necessarily ensure safer pedestrian conditions. However, its comfort score (0.86) remains high, suggesting a relatively smooth walking experience.

MOACO-WA achieves better attractiveness (0.62) and higher safety (0.21) than Dijkstra but at the cost of a longer route (2535.46m). Its comfort score (0.94) is the same as PB-MOACO, making it a viable alternative for pedestrians prioritizing both scenic and comfortable routes, though at the expense of accessibility.

PB-MOACO stands out as the most balanced algorithm, offering the highest safety score (0.31) while matching MOACO-WA in comfort (0.94). It achieves a competitive attractiveness score (0.67) while maintaining better accessibility (2323.10m) than MOACO-WA. These results suggest that PB-MOACO provides the most well-rounded solution for pedestrian route planning, particularly for scenarios where attractiveness and comfort are prioritized while maintaining reasonable accessibility and safety.

For Use Case 2**,** which includes the route from Green Square Community Hall to Waterloo Railway Station**,** the three algorithms were assessed based on the same four criteria.

- **Which Algorithm Performed Best for Commuters?**

Overall, PB-MOACO emerges as the most effective algorithm for pedestrian route planning in commuter contexts, offering an optimal balance between safety, comfort, accessibility, and attractiveness. Its ability to maintain high comfort (0.94) while achieving the highest safety score (0.31) makes it particularly suitable for urban environments where pedestrian well-being is a priority.

Furthermore, PB-MOACO's moderate accessibility (2323.10m) ensures that pedestrians are not subjected to excessively long routes while still benefiting from enhanced scenic value and urban amenities. Unlike Dijkstra, which prioritizes efficiency over user experience, and MOACO-WA, which sacrifices accessibility for aesthetics, PB-MOACO provides a comprehensive and user-centric approach that considers both practicality and pedestrian preferences.

This adaptability makes PB-MOACO particularly valuable for pedestrian-friendly city planning, walkability improvement projects, and tourism-focused route optimization. It allows urban planners and decision-makers to design routes that enhance pedestrian safety while ensuring engaging and comfortable travel experiences.

➢ **Figures and Visual Comparisons**

Figure 6.21 illustrates the generated paths for each algorithm, highlighting differences in routing choices between PB-MOACO, MOACO-WA, and Dijkstra's method.

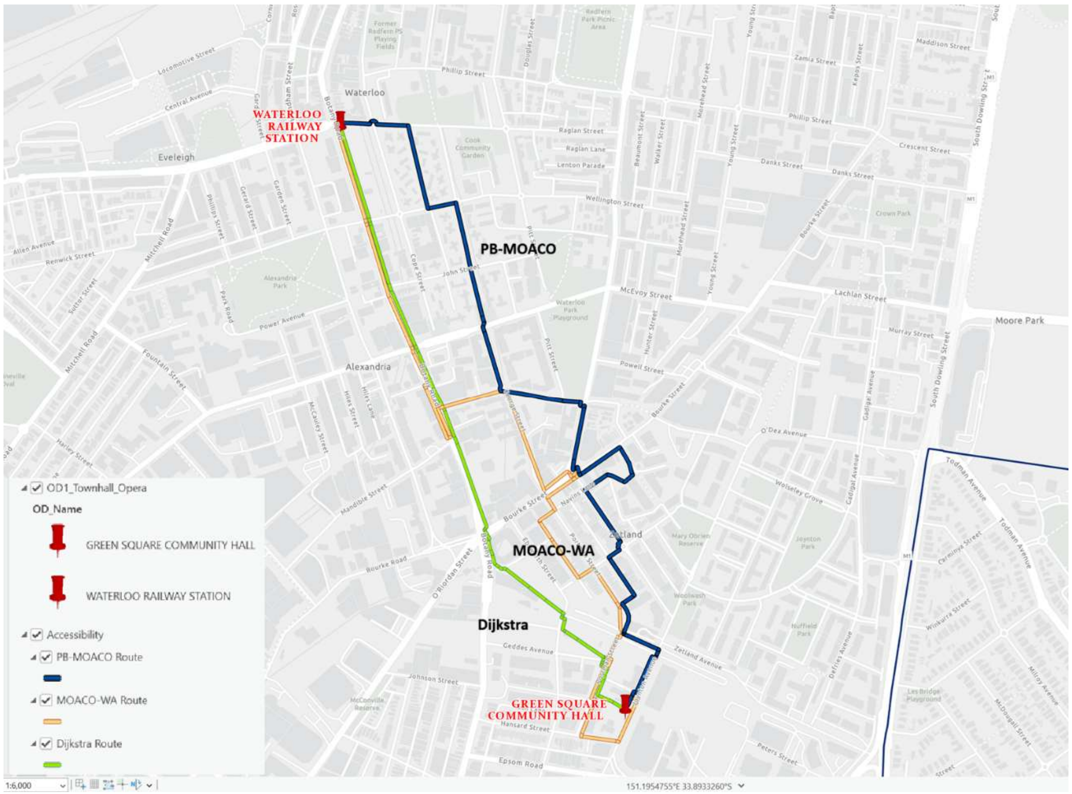


Figure 6.21 map of the three generated path between origin and destinations points.

Figure 6.22 provides a safety comparison, where Dijkstra performs best, while PB-MOACO and MOACO-WA score significantly lower.

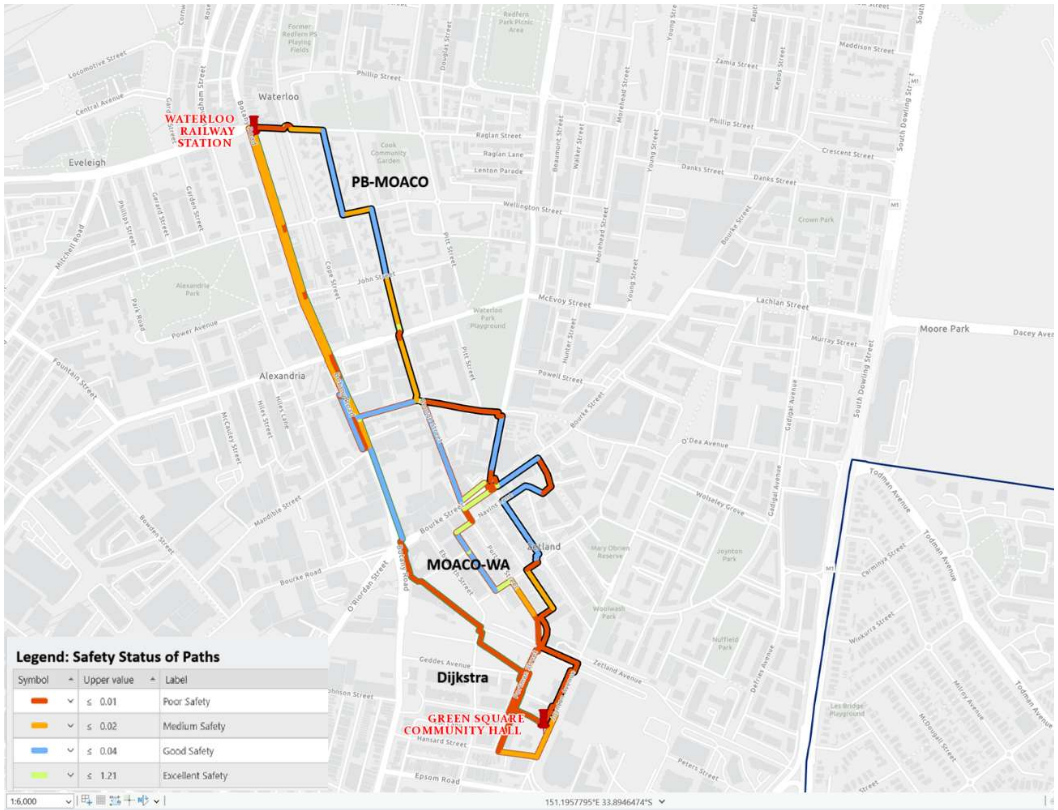


Figure 6.22 Safety comparison of three different routing approaches —PB-MOACO, MOACO-WA, Dijkstra

Figure 6.23 visualizes comfort differences, showcasing how PB-MOACO optimizes pedestrian experience, whereas MOACO-WA and Dijkstra have moderate variations in terrain difficulty.

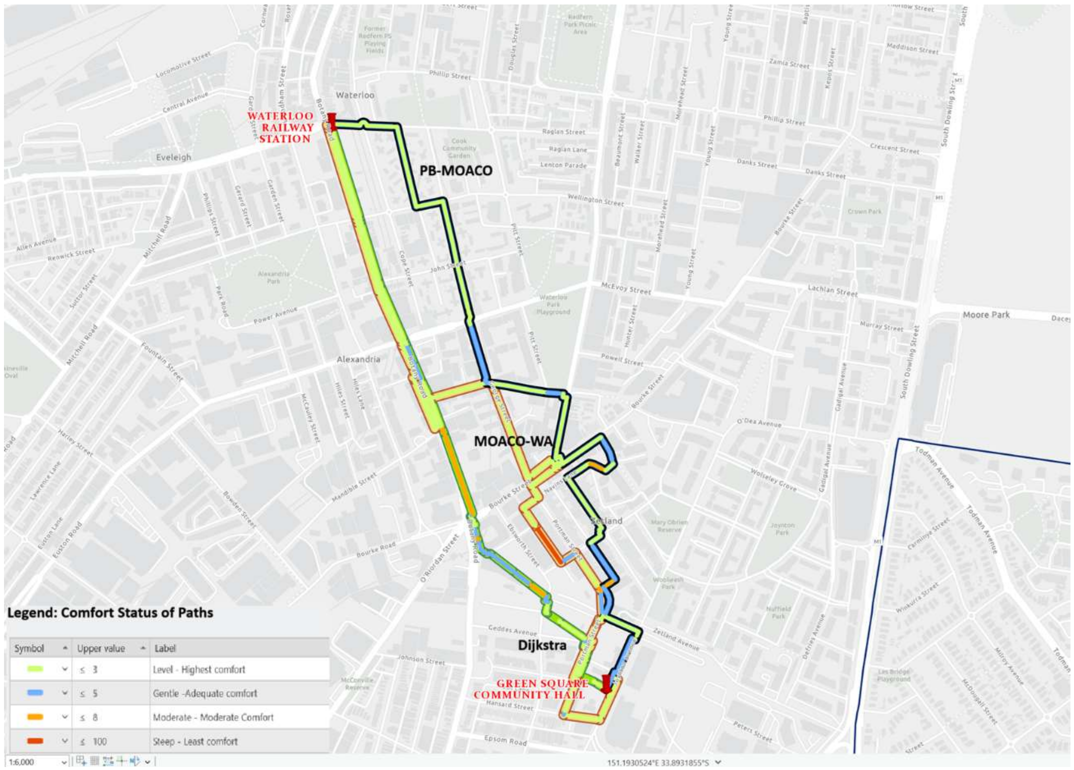


Figure 6.23 Comfort comparison of three different routing approaches — MOACO-WA, PB-MOACO, and Dijkstra's algorithm

Figure 6.24 compares urban land use distributions across the three algorithms, demonstrating how PB-MOACO and MOACO-WA emphasize scenic and cultural POIs more effectively than Dijkstra.

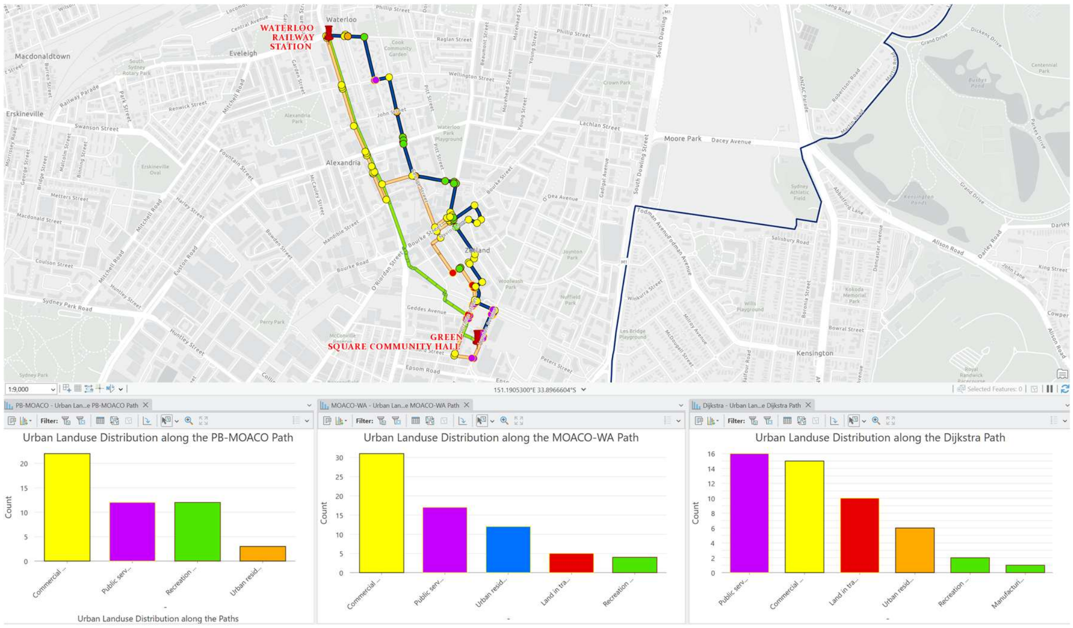


Figure 6.24 Comparison of urban land use distributions for three different routing approaches — MOACO-WA, PB-MOACO, and Dijkstra's algorithm.

6.12 Algorithms Performance Evaluation in Overall

Evaluating the accuracy and overall effectiveness of our pedestrian route planning framework, we focused on four key aspects: route length versus multi-criteria balance, computational efficiency, sensitivity to parameters, and stability/consistency. The following quantitative comparison in table 6.17 provides a clear illustration of how each algorithm performance. The quantitative numbers presented in this table are normalized scores (ranging from 0 to 1) that represent relative performance measures.

Table 6.17 Performance Evaluation Metrics for Dijkstra, MOACO-WA, and PB-MOACO Algorithms

Metric	Dijkstra	MOACO-WA	PB-MOACO
Route Length vs. Criteria Balance	0.25 – produces the shortest route but offers a poor balance of safety, comfort, attractiveness, and accessibility.	0.60 – achieves a more balanced route, though at the cost of longer distances.	0.85 – best multi-objective balance with adaptive trade-offs, despite longer routes.
Computational Efficiency	0.95 – very fast and efficient for single-objective tasks.	0.65 – slower due to the stochastic nature of ACO, with increased computational demand for balancing objectives.	0.60 – slower than Dijkstra; however, its scalability makes it more suitable for complex, real-world applications.
Sensitivity to Parameters	N/A – Dijkstra is designed for single-objective optimization, so parameter sensitivity is not applicable.	0.55 – moderately sensitive; performance can vary as weights and pheromone parameters change.	0.80 – exhibits lower sensitivity, maintaining robust performance with minor fluctuations in parameter settings.
Stability/Consistency	0.90 – high consistency, reliably reproducing the same shortest path.	0.70 – moderate consistency due to	0.90 – high consistency achieved by adaptive

		inherent randomness in the algorithm.	mechanisms that stabilize route outcomes across iterations.

6.13 Chapter Summary

➢ **Objective**:

This chapter evaluates the adaptability and effectiveness of developed pedestrian route planning algorithm in real-world urban environments, focusing on Sydney, Australia. It integrates spatial datasets and tests the algorithm across diverse scenarios to balance safety, comfort, accessibility, and attractiveness.

➢ **Study Area**:

- **City of Sydney**: Chosen for its diverse landscapes (CBD, residential zones, parks, waterfronts) and robust pedestrian infrastructure. The area includes 26.15 km² of mixed land use, enabling testing across varied terrains and pedestrian needs.

➢ **Spatial Datasets**:

1. **Pedestrian Network**: Extracted from OpenStreetMap, encompassing walkways, streets, and cycleways.
2. **Land Use**: Classified into categories (e.g., recreational, residential, commercial) to assess attractiveness.
3. **Street Lighting**: Analyzed for safety and nighttime visibility.
4. **Digital Elevation Model (DEM)**: Assessed terrain slope for comfort. These datasets were integrated into a multi-dimensional network for analysis in Python using GIS tools.

➢ **Methodology**:

- **Algorithms Tested**:
    1. **PB-MOACO** (Pareto-Based Multi-Objective Ant Colony Optimization): Generates Pareto-optimal routes balancing multiple criteria.

2. **MOACO-WA** (Weighted Aggregation): Combines objectives into a single cost function.
3. **Dijkstra's Algorithm**: Prioritizes shortest paths.

- **Case Studies**:
    - **Tourists in CBD**: Prioritized attractiveness (45%) and comfort (20%) over accessibility.
    - **Commuters in Suburbs**: Emphasized safety (30%) and accessibility (40%).

➢ **Results:**

1. **Tourist Use Case (CBD)**:
    - **PB-MOACO** excelled in attractiveness (0.95) and comfort (0.85), offering scenic routes but with lower safety (0.13).
    - **MOACO-WA** balanced attractiveness (0.83) and accessibility but was less safe.
    - **Dijkstra** provided the shortest path (2.2 km) but scored lowest in attractiveness (0.72).
2. **Commuter Use Case (Suburbs)**:
    - **PB-MOACO** achieved the best safety (0.31) and comfort (0.94) with moderate accessibility (2.3 km).
    - **MOACO-WA** improved safety (0.21) but was less efficient (2.5 km).
    - **Dijkstra** was fastest (1.7 km) but least safe (0.11) and attractive.

➢ **Performance Evaluation**:

- **PB-MOACO**: Best multi-criteria balance (0.85/1) and faster than MOACO-WA in case of changing user preferences weights.
- **Dijkstra**: Fastest (0.95/1) but limited to single-objective optimization.

- **MOACO-WA**: Moderate balance (0.60/1) with stochastic variability and slower if user preferences change.

In summary, PB-MOACO is optimal for scenarios requiring trade-offs between safety, comfort, and aesthetics, making it suitable for tourists and urban planners. Dijkstra remains ideal for efficiency-focused commuters. The study underscores the importance of context-specific algorithm selection and highlights PB-MOACO's robustness in complex, multi-objective route planning. Future work could enhance computational efficiency and safety parameter integration.

CHAPTER 7

CONCLUSIONS AND FUTURE WORKS

7.1 Conclusions

This thesis has provided a comprehensive investigation into pedestrian route planning by expanding and customizing two variants of Ant Colony Optimization (PB-MOACO and MOACO-WA) to address our novel multi-objective problem. Alongside these ACO-based solutions, the traditional Dijkstra algorithm was used for performance evaluation. The key conclusions are as follows:

The ACO-based solutions outperformed the traditional Dijkstra's algorithm in providing more personalized and user-centric routing experiences for pedestrians. It was able to cater to the diverse needs and preferences of pedestrians beyond just distance optimization.

- **Key Findings:**

Safety & Comfort: PB-MOACO consistently generated the safest and most comfortable routes, outperforming MOACO-WA and Dijkstra's algorithm by integrating real-world pedestrian safety factors and terrain conditions.

Attractiveness: PB-MOACO prioritizes scenic routes and points of interest, making it highly appealing for pedestrians who value urban aesthetics. MOACO-WA offers a balanced approach, while Dijkstra focuses purely on minimizing distance.

Accessibility & Efficiency: Dijkstra produces the shortest paths, optimizing for directness, but lacks personalization. PB-MOACO and MOACO-WA offer more context-aware routes, incorporating multiple objectives at the cost of slightly increased path length.

Performance & Versatility: PB-MOACO emerges as the most robust algorithm, balancing all objectives effectively. It demonstrates superior adaptability to user preferences, making it ideal for real-world pedestrian navigation systems.

- **Contributions & Impact:**

This research advances multi-objective pedestrian route optimization through several key contributions

Novel Multi-Objectives Optimization Framework: Developed PB-MOACO, a metaheuristic approach that optimizes multiple conflicting objectives, improving pedestrian experience beyond traditional shortest-path models.

Advanced GIS-Based Methodology: Established a multi-dimensional pedestrian network model, ensuring a more accurate representation of urban environments for pedestrian routing.

Metaheuristic Algorithm Design: Demonstrated how ant colony optimization can be adapted for pedestrian route planning, incorporating user-defined preferences dynamically.

Real-World Deployment and Evaluation: Implemented and tested the proposed system in Sydney’s urban network, validating its performance against real pedestrian mobility patterns.

- **Final Remarks:**

This thesis presents a comprehensive and practical approach to pedestrian route planning, demonstrating that PB-MOACO significantly enhances user experience by prioritizing safety, comfort, and attractiveness while maintaining accessibility. The study’s findings underscore the importance of personalized route planning and provide a solid foundation for future developments in pedestrian navigation systems.

However, further research is needed to improve scalability, incorporate real-time data, and refine algorithmic efficiency for broader deployment across diverse urban environments.

7.2 Future Works

Building on the findings of this research, several promising **directions for future work** can enhance pedestrian route optimization systems:

1. **Algorithm Enhancements & Hybridization**
    - Refining PB-MOACO: Further tuning of pheromone update rules, weighting schemes, and parameter control could improve algorithm efficiency.
    - Hybrid Multi-Objective Approaches: Exploring combinations of PB-MOACO with other metaheuristics (e.g., NSGA-II, SEMO) could enhance convergence speed and diversity of solutions.
2. **Integration of Real-Time Data**
    - Incorporating real-time pedestrian traffic, weather conditions, and temporary road closures would make the routing system more adaptive.
    - Crowdsourced data (e.g., from mobile apps or smart sensors) can provide up-to-date insights into pedestrian preferences and obstacles.
3. **Multi-Modal Urban Mobility**
    - Integrating pedestrian routes with public transport, cycling, and ride-sharing can enable seamless multi-modal journey planning.
    - Optimizing transfer points between transport modes would improve travel efficiency in complex urban networks.
4. **Expanding Deployment & Field Testing**
    - Extending testing to other cities (e.g., Toronto, Melbourne) would assess scalability and adaptability to different urban environments.
    - Conducting real-world field studies with pedestrian users would provide qualitative feedback to enhance system usability.

5. **User-Centric System & Interactive Interfaces**

   - Developing a mobile/web-based application with an intuitive user interface would allow pedestrians to dynamically adjust their preferences and receive personalized route recommendations.
   - Incorporating interactive feedback mechanisms would help refine route suggestions based on real-time user input.

6. **System Performance & Scalability**

   - Optimizing computational efficiency through parallel processing or cloud-based implementations could improve real-time processing capability.
   - Enhancing spatial database management for dynamic updates would reduce computational overhead in large-scale deployments.

➢ **Final Thoughts on Future Work**

This research provides a solid foundation for future advancements in pedestrian route planning. The outlined enhancements, integrations, and optimizations will contribute to developing scalable, intelligent, and highly adaptive pedestrian navigation systems that align with real-world urban mobility needs.

By expanding the scope to multi-modal transport, real-time data, and user-driven customization, pedestrian route planning can evolve into a truly intelligent and context-aware system, enhancing urban mobility for all.

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