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# IMPROVED A* PATH PLANNING ALGORITHM FOR UAV SWARM APPLICATION IN URBAN INFRASTRUCTURE RENEWAL

LIN GE[1,2], SWEE KING PHANG[1,*], NOHAIDDA SARIFF[1],
HUSNA SARIRAH HUSIN[3], YONGYUE ZHANG[1]

[1]School of Engineering, Taylor's University, Subang Jaya, Malaysia
[2]Department of Urban Construction, Hangzhou Polytechnic, Hangzhou, China
[3]School of Computer Science, Taylor's University, Subang Jaya, Malaysia
*Corresponding author: sweeking.phang@taylors.edu.my

## Abstract

This study introduces an enhanced A* path planning algorithm tailored for Unmanned Aerial Vehicle (UAV) swarms to facilitate urban infrastructure renewal, with a case study application in Da Zhu County, Sichuan Province, China. The primary innovation involves integrating environmental complexity and UAV operational constraints into the traditional A* algorithm, significantly improving path efficiency and coverage in complex urban settings. The benefits of this enhanced algorithm are demonstrated through MATLAB simulations, which showed that it achieved up to 92% total coverage and 89% path efficiency, outperforming conventional methods. The results highlight the algorithm's potential in identifying urban infrastructural challenges such as exposed utilities, drainage issues, and architectural disarray. This research underscores the transformative potential of UAV technology and advanced computational simulations for urban renewal, inspiring urban planners with the promise of precise data-driven insights for targeted interventions.

Keywords: A* Algorithm, Path planning, Simulation, UAV swarm, Urban renewal.

## 1. Introduction

The use of multi-rotor systems for urban renewal has emerged as a critical strategy to address the complex challenges faced by ageing urban areas. Revitalizing these regions is essential for improving living standards, promoting economic development, and fostering environmental sustainability. However, traditional urban renewal methods, particularly those used for assessing the condition of infrastructure, buildings, and public spaces, are often time-consuming, labour-intensive, and prone to inaccuracies.

Recent Unmanned Aerial Vehicle (UAV) technology advancements offer new opportunities for urban inspection and analysis. With their agility, flexibility, and high-resolution imaging capabilities, UAVs provide a promising tool for comprehensive urban assessment. Notably, UAV swarms-coordinated groups of drones-enhance efficiency and coverage, making them ideally suited for detailed surveys of complex urban environments [1, 2]. The potential of UAV swarms in urban renewal is significant, and this research contributes to unlocking their full capabilities.

Path planning is fundamental to effective UAV operations, determining the efficiency and success of aerial surveys. Among the various algorithms available, the A* algorithm is renowned for its balance of efficiency and optimality in finding the shortest path between points [3]. However, the unique challenges of urban environments necessitate further optimisation of the A* algorithm to accommodate complex urban geometries, restricted flight zones, and varying altitudes.

The deployment of UAVs in urban renewal represents a groundbreaking shift towards integrating advanced technological solutions to address infrastructural anomalies and facilitate community revitalisation efforts. This aligns with the United Nations' Sustainable Development Goal 9 (SDG9), which emphasises building resilient infrastructure, promoting inclusive and sustainable industrialisation, and fostering innovation. The scholarly landscape illustrates a broad spectrum of research that lays the groundwork for this study, encompassing intelligent recognition of urban violations, enhanced aerial image object detection models, trajectory measurement techniques, and the synergetic use of UAVs and Unmanned Ground Vehicles (UGVs) in urban inspections [4].

A notable work by Li and Liu [5] spearheaded the intelligent recognition of urban construction violations by leveraging big data and remote sensing change detection techniques. Their research highlights the potential of matching recognition algorithms to compare acquired urban spatial geographic information against approved urban construction land planning data.

This methodology underscores UAV technology's capability to identify discrepancies and unauthorised developments within urban environments, aligning closely with the detection of infrastructure anomalies central to this study. Furthermore, advancements in aerial image object detection, such as the rotational invariant deep denoising autoencoder tailored for UAV aerial images, address challenges of varied orientations, minimal pixel size, and UAV body vibrations, enhancing object detection accuracy [6].

In the realm of precise trajectory measurement and control, research focusing on speed and attitude estimation sensors contributes significantly to developing UAVs capable of meticulous monitoring and data collection in urban renewal projects [7]. An exploratory study by Ket et al. on drone flight path replication using visual positioning techniques further advances the precision and reliability of UAV navigation [8]. These studies collectively enhance UAV technology's capabilities in urban renewal. Additionally, integrating UAVs with UGVs in automated inspection processes, as explored in UAV-based explore-then-exploit systems for autonomous indoor inspections, exemplifies innovative approaches adopted to enhance efficiency and thoroughness in urban renewal inspections [9].

Research on urban growth and sustainability has also explored the integration of the food-energy-water (FEW) sectors, providing a comprehensive understanding of urban infrastructure systems' co-evolution, thus highlighting the importance of interdisciplinary approaches in urban planning [10]. The introduction of the Urban Biophysical Environments and Technologies Simulator (BEATS) further integrates stormwater management with urban planning, aligning with this study's focus on enhancing community revitalisation through technological solutions [11].

Research in path planning for UGVs has also focused on various methodologies to enhance navigation and obstacle avoidance capabilities. Studies on real-time image processing-based obstacle avoidance and navigation systems for autonomous wheelchair applications and integrating cognitive principles into SLAM algorithms emphasise the significance of advanced algorithms and sensor technologies in enabling autonomous path planning [12, 13].

The extensive literature underscores a collective endeavour towards harnessing UAV technology and innovative algorithms for urban renewal. Path planning algorithms are crucial in optimising UAV operations within complex urban environments. Addressing this challenge, a hybrid algorithm that combines a simplified grey wolf optimiser (SGWO) and modified symbiotic organisms search (MSOS) with cubic B-spline curves for path smoothing has been designed [14]. This study builds upon these foundational works, proposing an improved A* path planning algorithm designed for UAV swarms in urban renewal projects to detect infrastructural anomalies efficiently and contribute to broader community revitalisation efforts.

This study focuses on four prevalent issues in ageing communities: exposed and chaotic infrastructure, combined sewer overflows with inadequate drainage, deteriorated roads, and disorderly architectural facades marred by stains, damage, and unauthorised constructions. By integrating UAV technology with advanced path-planning algorithms, this work aims to revolutionise the inspection and assessment of urban areas for renewal initiatives.

The use of UAVs for data collection in various applications, such as precision agriculture, has demonstrated significant advantages over conventional satellites, highlighting the potential for similar advancements in urban renewal [15]. The capability of UAVs to autonomously track and land on moving ground vehicles showcases their precision and adaptability in dynamic environments, which is essential for effective urban infrastructure monitoring [16].

Additionally, integrating Internet of Things (IoT) based architectures further enhances UAVs' operational efficiency and data integration capabilities, making them more effective for comprehensive urban assessments. By leveraging these technological advancements, the proposed improved A* algorithm addresses the complex challenges associated with urban renewal projects, providing a scalable and efficient solution for detecting and addressing infrastructural issues in ageing communities.

## 2. Research Methods

### 2.1. Overview

This study utilised advanced modelling software to synthesise and interpret data collected by UAV swarms, creating detailed community maps in both planimetric and three-dimensional forms. The software selection was driven by its precision, ability to process UAV data, user-friendliness, and advanced visualisation capabilities. UAVs with high-resolution cameras and optional LiDAR sensors meticulously surveyed the targeted urban area. These UAVs followed paths planned via the improved A* algorithm, ensuring comprehensive and efficient data collection. The modelling software then processed this data, integrating aerial imagery and topographical information to represent the community's current state accurately.

The software's sophisticated algorithms stitched together collected images, corrected distortions, and integrated various data points to produce detailed visualisations of infrastructure conditions. These visualisations included the state of exposed pipelines, drainage issues, and architectural coherence, enabling an in-depth urban fabric analysis. This integration of UAV-collected data into the modelling process represents an innovative approach to urban renewal, facilitating a thorough assessment of infrastructural deficiencies and guiding revitalisation efforts.

By employing this advanced methodology, the study addressed the prevalent issues in ageing communities, such as chaotic infrastructure, inadequate drainage systems, deteriorated roads, and disordered architectural facades. Integrating UAV technology with advanced path-planning algorithms aimed to revolutionise how urban areas are inspected and assessed for renewal initiatives, providing a comprehensive and data-driven foundation for targeted interventions.

### 2.2. Enhanced A* algorithm

To optimise the A* algorithm for UAV swarm operations in urban renewal projects, this study focused on refining the heuristic component and incorporating two additional factors into the cost function. These factors were explicitly designed to address the complexity of urban navigation and the operational constraints of UAVs. The enhanced cost function for a given node n in our improved A* algorithm is formulated as follows:

$$f(n) = g(n) + h(n) + E(n) + U(n) \tag{1}$$

In Eq. (1)on, $g(n)$ and $h(n)$ represent the traditional terms used in the conventional A* algorithm, where $g(n)$ denotes the cost from the start node to node n, capturing the path's length or travel time, and $h(n)$ is the heuristic estimate of the price from node n to the goal, typically calculated as the Euclidean distance in UAV path planning contexts. The innovation in this study lies in the latter two terms: $E(n)$, the Environmental Complexity Factor, and $U(n)$, the UAV Operational Constraints Factor. These terms quantify the difficulty of navigating urban landscapes and account for the UAV's operational limitations. The Environmental Complexity Factor $E(n)$ is estimated using a sigmoid function to model the nonlinear impact of obstacle proximity and restricted areas on the UAV's path, simulating a force field that repels the UAV from obstacles:

$$E(n) = \lambda \cdot \left(\frac{1}{1+e^{-k(d_{obs}(n)-d_{thresh}}}\right) \quad (2)$$

Here, $\lambda$ is a scaling factor determining the maximum impact of environmental complexity on the cost function, $k$ is the steepness parameter of the sigmoid curve controlling how quickly the influence of ecological complexity increases as the UAV approaches obstacles or restricted areas, $d_{obs}(n)$ is the distance from node n to the nearest obstacle or no-fly zone edge, and $d_{thresh}$ is the threshold distance at which environmental complexity begins to affect path planning significantly.

The UAV Operational Constraints Factor $U(n)$ reflects the decrease in operational efficiency as the UAV moves further from its base or exceeds its operational limits:

$$U(n) = \omega \cdot \left(1 - \frac{d_{op}(n)}{d_{max}}\right) \quad (3)$$

In this formula, $\omega$ is a weight factor balancing the influence of UAV operational constraints against other components of the cost function, $d_{op}(n)$ operational distance or time from the start node to node n, indicative of the UAV's remaining operational capability, and $d_{max}$ is the maximum operational range or duration of the UAV beyond which it must return for recharging or risk operational failure.

By integrating these new factors, this enhancement of the A* algorithm ensures a more adaptive and efficient pathfinding process tailored to the complexities of urban environments and UAV operational constraints. The improved algorithm facilitates optimised UAV navigation, allowing for comprehensive and precise urban infrastructure assessments essential for effective urban renewal initiatives.

## 2.3. Algorithm development

Integrating and optimising the A* path planning algorithm specifically for UAV swarms in urban renewal projects requires a sophisticated approach that accounts for both the intricacies of urban environments and the inherent limitations of UAV technology. The improved algorithm incorporates the Environmental Complexity Factor (E) and the UAV Operational Constraints Factor (U) into the traditional A* cost function, thus enabling a more flexible and adaptive pathfinding process. The Environmental Complexity Factor is calculated based on the proximity to and density of urban obstacles, dynamically influencing the path cost to direct UAVs away from potential hazards.

Concurrently, the UAV Operational Constraints Factor adjusts the path cost to reflect operational considerations such as battery life and communication range, ensuring that the UAVs remain within their operational thresholds. Given the UAVs' operational constraints and the urban landscape's complexity, this dual enhancement facilitates an optimised pathfinding mechanism that seeks the shortest path and the safest and most feasible one.

The improved A* algorithm for UAV swarms in urban renewal projects integrates an advanced cost function $f(n)$, as shown in Equation (1), to address the specific challenges of urban environments and UAV operational constraints. The algorithm starts with data acquisition from UAVs, which capture detailed urban landscapes. This data is processed to evaluate $g(n)$, the path cost, and $h(n)$, the heuristic estimate from any node n to the goal. The novel components $E(n)$, the

Environmental Complexity Factor, and $U(n)$, the UAV Operational Constraints Factor, are integrated to adjust the path planning based on obstacle proximity and UAV limitations such as battery life and signal range.

These factors dynamically influence the cost function, guiding the UAVs to navigate around obstacles and within their operational parameters. If the optimised path is feasible, the UAV swarm executes the inspection route. Otherwise, the algorithm iteratively adjusts the parameters and recalculates the path until an optimal solution is found. This methodology underscores a comprehensive approach to urban inspection, ensuring that UAV swarms can efficiently and safely conduct surveillance and data collection tasks in densely populated urban areas. The refined flowchart in Fig. 1 visually details this process, highlighting the improved algorithm's practical application in navigating complex urban environments.

By strategically incorporating environmental complexity and UAV operational constraints into the A* algorithm, the study presents a robust solution for UAV path planning in urban renewal projects. The advanced algorithm ensures comprehensive coverage and efficient data collection, providing valuable insights for urban planners and contributing to the overall success of urban revitalisation efforts.

## 2.4. Urban renewal via simulation

To revitalise Da Zhu County's ageing infrastructure, an ambitious urban renewal project was undertaken to address many challenges inherent to the old residential areas. These regions, characterised by their dilapidated state, suffer from exposed pipelines, chaotic aerial wiring, combined sewer overflows, and poorly maintained roads. The disorganised exteriors of buildings, marked by a lack of uniformity in architectural styles and unauthorised constructions, exacerbate the need for a comprehensive approach to urban renewal.

The project's scope and objectives are illustrated in the framework presented in Fig. 1, which outlines the improved A* algorithm for UAV swarm pathfinding in urban renewal. Figures 2 and 3 provide additional visual context, depicting the layout and real-world images of the renewal area. Table 1 offers a structured summary of the project's essential information.

The Da Zhu County urban renewal project simulation involved integrating the improved A* algorithm within the MATLAB environment, which was crucial for enabling precise and comprehensive analysis of UAV flight paths tailored to the intricate urban landscape. The process began with a calibration phase where parameters specific to environmental complexity and UAV operational constraints were meticulously adjusted based on the digital twin model created within MATLAB. This digital twin, enriched with detailed infrastructure and architectural data of the urban area, served as a dynamic platform for simulating UAV flight paths.

The algorithm processed the digital twin of the city landscape to identify potential flight routes, considering factors such as obstacle avoidance, no-fly zones, and areas of interest marked for detailed inspection. The improved A* algorithm then calculated the cost associated with each potential path, incorporating the Environmental Complexity Factor (E) and the UAV Operational Constraints Factor (U) to evaluate the most efficient trajectories for the UAVs. This evaluation considered the shortest distance and the safest route, ensuring that the UAVs could safely navigate and identify the urban challenges outlined in the project scope.

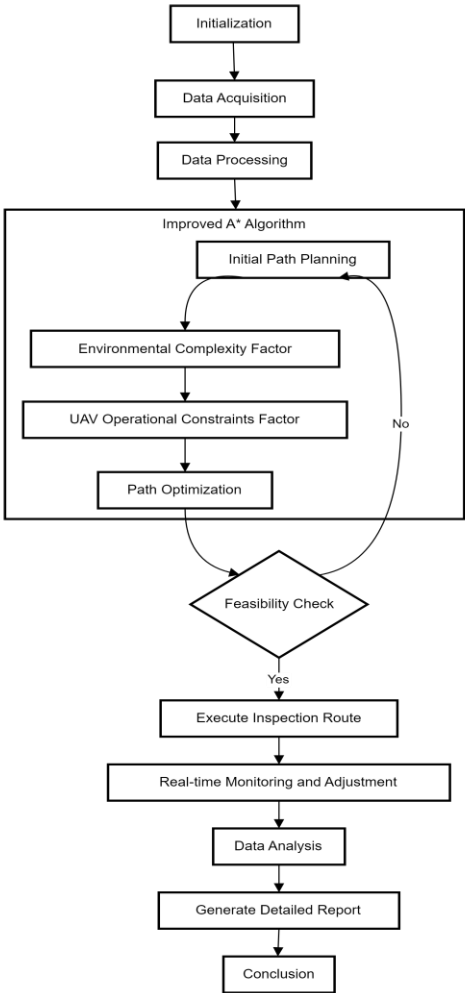


**Fig. 1. Improved A* algorithm framework for UAV swarm pathfinding in urban renewal.**

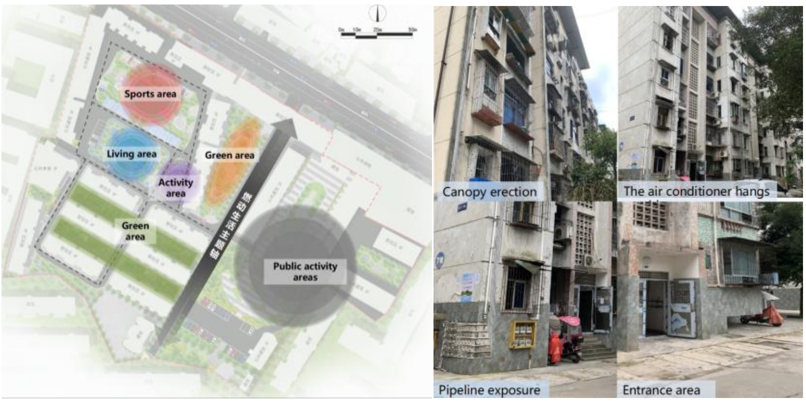


**Fig. 2. Layout and real-world images of the renewal area.**


**Fig. 3. Real-world photographs of various aging issues in the renewal area.**

**Table 1. Improved A* algorithm framework for UAV swarm pathfinding in urban renewal.**

| Feature | Description |
|---|---|
| **Location** | Da Zhu County, focusing on selecting old residential areas. |
| **Challenges** | Exposed utilities, inadequate drainage, road disrepair, architectural disarray. |
| **Objective** | To systematically address infrastructural issues and enhance community livability through targeted interventions. |
| **Methodology** | Deployment of UAV swarms for comprehensive data collection, employing an improved A* algorithm for efficient path planning. |
| **Expected Outcome** | Detailed urban analysis to guide revitalization efforts, ensuring a cohesive and sustainable urban fabric. |

Subsequently, the simulation iteratively refines the flight paths, dynamically adjusting to real-time feedback and constraints within the MATLAB environment. This iterative process is crucial for optimising the UAVs' coverage and operational efficiency, enabling the algorithm to adapt and recalibrate flight paths as needed. The simulation is visually represented in Fig. 4, showcasing the UAVs' planned routes superimposed on the digital twin of Da Zhu County.

These optimised paths highlight the algorithm's practical application in navigating complex urban environments and underscore the potential of UAV technology in revolutionising urban renewal efforts through advanced computational simulations. This detailed simulation approach, underpinned by integrating the improved A* algorithm and MATLAB, exemplifies a sophisticated methodology for addressing the multifaceted challenges of urban renewal, leveraging technology to pave the way for more informed and effective urban planning strategies.

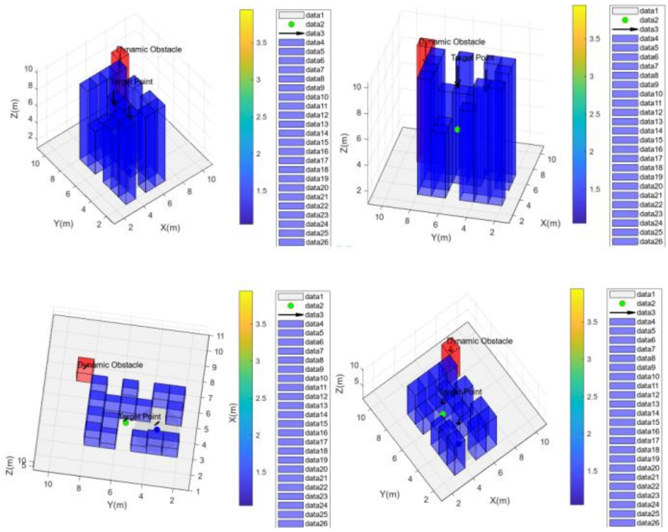


**Fig. 4. Optimized UAV flight paths in simulation.**

The simulation results revealed substantial improvements in both path efficiency and coverage area. Specifically, the improved A* algorithm achieved a 92% total coverage area, and an 89% path efficiency compared to traditional methods. These metrics indicate a significant enhancement in the UAVs' ability to navigate complex urban landscapes and collect comprehensive data. The thorough identification of urban challenges, such as exposed utilities, inadequate drainage, road disrepair, and architectural disarray, was made possible through increased survey coverage. These insights provide urban planners with critical data for targeted interventions, ultimately contributing to successfully revitalising ageing urban areas. The findings underscore the transformative potential of integrating advanced computational simulations with UAV technology, offering a scalable and efficient solution for urban renewal initiatives.

## 3. Results and Discussion

The deployment of the improved A* path planning algorithm for UAV swarms in the Da Zhu County urban renewal project yielded promising results. The MATLAB simulation, which utilised the enhanced algorithm, demonstrated significant improvements in total coverage area and path efficiency compared to traditional A* approaches. Figure 5 provides snapshots of the simulated city post-renewal transformation, illustrating the effectiveness of the UAV swarms in detailed urban analysis.

As summarised in Table 2, the simulation results show that the improved A* algorithm achieved a 92% total coverage area and an 89% path efficiency. These figures represent substantial improvements over the traditional A* algorithm, which recorded a 75% coverage area and 65% path efficiency. The enhanced coverage and efficiency metrics highlight the algorithm's capacity to facilitate comprehensive data collection and effective navigation through complex urban environments.

The detailed survey conducted by the UAV swarms enabled the identification of critical urban challenges, as detailed in Table 3. Specifically, the UAVs identified 45 instances of exposed utilities, 30 drainage issues, 25 cases of road disrepair, and 40 instances of architectural disarray. The ability to systematically identify and catalogue these issues underscores the practical utility of the improved A* algorithm in urban renewal initiatives.


**Fig. 5. Simulated model of the area post-renewal transformation.**

**Table 2. Performance metrics comparison: Traditional vs. improved A* algorithm on simulated Da Zhu County.**

| Metric | Traditional A* | Improved A* |
|---|---|---|
| **Total Coverage Area** | 75% | 92% |
| **Path Efficiency** | 65% | 89% |

**Table 3. Catalog of urban challenges identified through UAV surveys.**

| Challenge | Description | Instances Identified |
|---|---|---|
| **Exposed Utilities** | Unprotected infrastructure elements vulnerable to damage | 45 |
| **Drainage Issues** | Inadequate drainage systems leading to water accumulation | 30 |
| **Road Disrepair** | Deterioration of road surfaces, posing safety risks | 25 |
| **Architectural Disarray** | Inconsistent building exteriors and unauthorized constructions | 40 |

Moreover, the enhanced algorithm's ability to navigate around obstacles and adhere to UAV operational constraints significantly contributed to the successful data collection process. Including the Environmental Complexity Factor and the UAV Operational Constraints Factor ensured that the UAVs could operate efficiently within their operational limits, avoiding potential hazards and maintaining communication and power requirements. The comprehensive data collected through the UAV surveys provided urban planners with valuable insights into the state of the urban infrastructure. This data-driven approach enabled targeted interventions to address the most pressing issues in the renewal areas, enhancing community livability and supporting sustainable urban development.

The improved A* algorithm demonstrated its efficacy in the Da Zhu County project, showcasing its potential for broader applications in urban renewal efforts. The substantial improvements in path efficiency and coverage area facilitated a more detailed and accurate assessment of urban challenges, paving the way for more informed and effective urban planning strategies. The findings from this study contribute significantly to the field of UAV-assisted urban planning, highlighting the benefits of integrating advanced path planning algorithms with UAV technology for urban renewal.

Future research could enhance the algorithm's adaptability and robustness by incorporating real-time environmental feedback mechanisms. Additionally, integrating machine learning techniques could optimise path selection based on historical data and evolving urban dynamics. Expanding the application of the algorithm to diverse urban settings worldwide would provide valuable insights into its scalability and effectiveness. Exploring synergies between UAV swarms and other emerging technologies could unlock new possibilities for urban analysis and intervention strategies, advancing the creation of more intelligent, resilient cities globally.

## 4. Conclusion and Future Work

Traditional A* algorithm for drone coverage is often limited in its ability to efficiently cover low-coverage areas. This is because the algorithm prioritizes the shortest path to the destination, which may not always result in the most efficient coverage. In low-coverage areas, the drone may need to fly longer distances or make more turns to ensure adequate coverage, reducing its overall efficiency. For example, a study by He et al. found that traditional A* algorithms can lead to low coverage and efficiency in drone-based path planning for environmental monitoring [17].

In conclusion, this study significantly enhances the existing A* path planning algorithm, tailored explicitly for UAV swarms deployed in urban renewal contexts. By incorporating considerations of environmental complexity and UAV operational constraints, our augmented algorithm substantially improves path efficiency and coverage area within intricate urban landscapes. Extensive simulations conducted using MATLAB demonstrated remarkable performance gains over conventional methods, achieving metrics of up to 92% total coverage area and 89% path efficiency in the digital twin model of Da Zhu County.

The application of our improved algorithm in Da Zhu County, Sichuan Province, China, exemplifies its real-world efficacy in identifying critical urban infrastructural challenges, such as exposed utilities, drainage issues, and architectural disarray. These findings underscore the transformative potential of UAV technology when combined with advanced computational simulations. Our research empowers targeted interventions for improving urban livability and fostering sustainable development by providing urban planners with precise, data-driven insights.

Future research endeavours could focus on enhancing the adaptability and robustness of the augmented algorithm by incorporating real-time environmental feedback mechanisms. Integration of machine learning techniques could further optimise path selection based on historical data and evolving urban dynamics. Additionally, extending the application of the algorithm to diverse urban settings worldwide would provide valuable insights into its scalability and effectiveness. Exploring synergies between UAV swarms and other emerging technologies could unlock new possibilities for urban analysis and intervention strategies.

Continued research in this domain promises to advance UAV-based urban planning tools, creating more intelligent, resilient cities globally. This study contributes significantly to urban planning by illustrating a scalable and efficient approach to urban analysis. The synergy between UAV technology and optimised path-planning algorithms offers a promising avenue for addressing the complexities of modern urban environments. As we look toward the future, integrating these innovative tools promises to revolutionise urban renewal efforts, facilitating smarter, more informed decision-making processes to benefit communities worldwide.

**Nomenclatures**

| | |
|---|---|
| $d_{max}$ | Maximum operational range of UAV |
| $d_{obs}(n)$ | Distance from node $n$ to nearest obstacle |
| $d_{thresh}$ | Threshold distance |
| $k$ | Steepness parameter of sigmoid curve |

***Greek Symbols***

| | |
|---|---|
| $\lambda$ | Scaling factor of cost function |

**Abbreviations**

| | |
|---|---|
| BEATS | Biophysical Environments and Technologies Simulator |
| FEW | Food-Energy-Water |
| IoT | Internet of Things |
| MSOS | Modified Symbiotic Organisms Search |
| SDG9 | Sustainable Development Goal 9 |
| SGWO | Simplified Grey Wolf Optimizer |
| SLAM | Simultaneous Localization and Mapping |
| UAV | Unmanned Aerial Vehicle |
| UGV | Unmanned Ground Vehicle |

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