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A framework for the optimal deployment of police drones based on street-level crime risk

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ABSTRACT

Drones are increasingly adopted for policing in many countries, as they can aid police officers to detect hazards and respond to incidents with timely and low-cost services. However, the planning and deployment of police drones are subject to several challenges, including the proper distance metric for drone flying and the risk-based location optimisation of drone base stations. This study proposes a new framework that enables the optimal deployment of police drones to address crime risk issues on urban street networks. This risk-based decision framework takes into account three potential distance metrics that regulate and shape the flying routes of drones, which in turn affects the optimal location of drone base stations. In addition, this framework takes into account the major risk constraints of flying drones in urban areas, including domestic privacy and elevation. The proposed risk-based decision framework is validated using the real case study of Liverpool with historical crime data and street network layouts. The findings contribute to the operations and management of police drones in urban areas and shift the paradigm of policing drones towards a risk-based regime.

1. Introduction

Unmanned aerial vehicles (UAVs) (also called drones) have been invented and continuously deployed in military operations (Wang, Zhou, Xing, Li, & Yang, 2023; Zhu, Zhu, Yan, & Peng, 2021). In recent decades, they have witnessed increased adoption in a wide range of civil applications (Finn & Wright, 2012), including remote sensing, goods delivery, surveillance, and medical aid (Feng, Murray, & Church, 2021; Gao, Chen, & Haworth, 2023; Pulver & Wei, 2018; Zhu, Yan, Peng, & Zhang, 2020). Police teams in various countries have been testing the use of drones for routine patrolling and emergency response (Finn & Wright, 2012; Kim & Davidson, 2015), as drones are capable of providing timely services to staff with low risk. Moreover, the use of police drones contributes to keeping the service at a reasonably low cost and high efficiency (Beg, Qureshi, Sheltami, & Yasar, 2021), which is especially important as the public sectors in many countries have been facing financial constraints. As an example, in Switzerland, camera equipment drones have become standardised tools for policing, serving various purposes such as visually preserving crime scenes, responding to kidnapping and terrorist-related incidents, and identifying criminals on the run. Police drones have introduced innovative approaches to policing and crime detection, incorporating aerial perspectives into policing (Klauser, 2022). Despite these advantages and case studies, using drones for police purposes based on crime data and risk levels is still in an early stage and is subject to several challenges. For instance, most of the existing studies of police drones assume that drones fly in straight lines between locations and follow a Euclidean distance, which is unrealistic in urban areas. Specifically, in urban areas, the flying routes of drones are restricted by a range of factors, including government regulations, no-fly zones, buildings, transport facilities, and domestic privacy concerns (Pang, Hu, Dai, & Low, 2022). Indeed, these factors increase the complexity of drone deployment and lead to new challenges, such as the location selection of drone base stations and route planning in urban areas. These issues should be tackled before the widespread deployment of police drones.

Although existing studies have proposed location-allocation models that determine the optimal locations of drone base stations, two significant research gaps exist in the literature. First, in most studies, the demand targets that are served by drones are well-defined discrete points, such as the locations of historical incidents (Claesson et al., 2016; Pulver & Wei, 2018) and the geometric/population-weighted centroids of census areas (Gao, Jiang, et al., 2023; Ozceylan, Ozkan, Kabak, &

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Dagdeviren, 2022). Recent research has also investigated a continuous surface of distributed demands. However, the distributed demands along street networks have not been taken into account, yet are critical in the domain of urban crime detection and response. Second, most studies presume that drones fly in straight lines and follow a Euclidean distance. This is not realistic for drone deployment in an urban built environment, and various distance metrics need to be investigated and compared in the planning of drone services for future crime risk control.

To address these research gaps, this study aims to develop a novel methodology facilitating the optimal deployment of police drones in response to crimes on street networks, using crime data and risk levels as key factors. The main contributions include considering street-level crime risk, testing different distance measures for drones' location selection, and combining police patrols with drones based on crime data and risk levels. A real-world case study in Liverpool demonstrates how this approach can improve the use of police drones in urban areas, offering potential benefits for future drone operations and management.

The remainder of this paper is organised as follows. Section 2 provides a comprehensive review of studies using drones for police patrol and the location selection of drone base stations in different applications. Section 3 presents the methodology and the key methods. Section 4 details the case study area and relevant datasets. Section 5 presents the results with different distance metrics and discusses the findings and implications. Finally, Section 6 concludes this paper by summarising the key findings and discussing future research directions.

2. Literature review

In this section, a systematic review is carried out regarding drone patrolling, police patrolling, and the location selection of drone base stations. Specifically, this section will summarise the state-of-the-art research regarding the methods and applications, identify the research gaps, and outline the contributions of this paper.

2.1. Drone patrolling

A systematic review was conducted by the Web of Science (WoS) Core Collection in May 2022 to retrieve all publications from 1990 to 2022 relating to the topic of 'drone patrolling'. A total of 45 publications were retrieved. Only seven peer-reviewed journal papers concerning the algorithms and applications of drone patrolling were retained. These include border surveillance patrolling (2 papers), power line inspection (1 paper), air-ground cooperation patrolling of drones and police vehicles (1 paper), the cooperation of vehicles and drones to solve the limited endurance problem (1 paper), the cooperation of trucks and drones to conduct forest monitoring (1 paper), three-dimensional (3D) navigation algorithms of drones (1 paper), and improving the accuracy of drones on autonomous straight take-off (1 paper). These selected papers are presented in detail as follows. Luo, Zhang, Wang, Wang, and Meng (2019) proposed a Traffic Patrolling Routing Problem with Drones (TPRP-D) to solve the optimal routes for limited and fixed tasks with a double-layer arc routing problem and two-stage heuristic method. Liu et al. (2021) combined a whale algorithm and the chaos theory to find the best plans for multiple drones in border patrol tasks under different complex environments. Ahmadian, Lim, Torabbeigi, and Kim (2022) put forward a drone surveillance system with wireless battery charging and a multi-objective Mixed-Integer Non-Linear Programming (MINLP) model to optimise the cooperation of multiple drones and the charging system for smart border patrolling. Momeni, Soleimani, Shahparvari, and Afshar-Nadjafi (2022) developed a multi-objective mixed-integer programming method to find the trade-off of the cooperative patrolling of trucks and drones for bushfire prevention and rescue. Yang, Ding, and Wang (2021) investigated air-ground cooperative patrolling using drones and police cars, proposed a UAV-Police Vehicle Cooperative Patrol Algorithm (U-PVCPA), and combined speed and hovering time to simulate the different cases and solve the patrol tasks. Giuseppi, Germana, Fiorini, DelliPriscoli, and Pietrabissa (2021) designed a drone patrolling system to locate the fireplace and realise early fire prevention based on the real estimation index, different factors, and dynamic Voronoi Tessellation. Chang, Tsai, Lu, and Lai (2020) proposed a new deep reinforcement learning method to analyse the performance and improve the control of drones flying during patrolling. Ming and Huang (2021) put forward a 3D corn-based navigational method to realise the anti-collision among the crowed-spaced 3D obstacles for future UAV operations. In summary, the literature addresses the diverse approaches and techniques employed in drone patrolling, with an emphasis on routing, navigation, and operations. However, there appears to be a gap in integrating the selection of drone base station locations into these studies.

2.2. Drones for policing

A total of 82 peer-reviewed journal papers are retrieved by using the topic of "police drones" from the WoS. Following the abstract and content screening, eight papers are selected for further review. Salter (2014) explored the history and relationship between drones, wars, and policing, as well as the legality of drones from military, public, and private perspectives. The policing and surveillance from the spatial dimension were conducted based on professional drone users, including public and private, in Switzerland (Klauser, 2021). This paper discussed the frequency of drone usage, restrictive factors, the advantages of drone usage, and the legal framework, shedding light on the importance and utility of police drones. Additionally, Klauser (2022) developed the theoretical possibility of a 3D model, highlighting the spatial aspects of policing, surveillance, and power. This study conducts theory research without mathematical models. The deployment of drones was analysed to explore the recognition possibility of targets, criminal suspects, and missing people from the perspective of cognitive psychology (Fysh & Bindemann, 2018). The study took into account face, body, and motion identification to assess the success rate of aiding the police and recommended the inclusion of drone image analysts for criminal identification. Furthermore, drone power is discussed from four perspectives: environmental, humanitarianism, policing, and war (Fish & Richardson, 2022). The biodiversity conservation, health services, police forces, and military factors were combined to emphasise the effectiveness of drone power. Drones were applied to aid the police force in crime scene surveillance (Bucknell & Bassindale, 2017). The analysis considered factors such as height, distance, and image quality to determine optimal monitoring performance, specifically focusing on indoor environments. Addressing the issue of police pursuits, Christie (2020) highlighted how the use of drones could help reduce injuries and risks based on a dataset from London. The study examined various influential risk factors and demonstrated that combining drones with police efforts could effectively control crime rates. The air-ground cooperation patrolling problem was proposed to address the uncertainty of patrol environment and resources (Yang et al., 2021). The generic algorithms were applied to discover the optimal allocation of multiple drones and police vehicles, ultimately improving the capability of emergency response.

In summary, the reviewed literature covers a range of topics related to police drones, including their historical and legal aspects, spatial dimensions, cognitive psychology implications, power considerations, crime scene surveillance, injury reduction in police pursuits, and air-ground cooperation. However, there remains a research gap in systematically comparing different distance metrics for police drone deployment and exploring the potential of police drones for street-level crime detection. To the best of our knowledge, no previous research has specifically investigated the use of police drones for street-level crime detection.

2.3. Location selection of drone base stations

A number of studies have emerged in the field of determining optimal locations for drone base stations. These studies consider various factors and constraints that influence drone services, such as distributed demand, demand uncertainty, wind speed, and critical service time in medical aid scenarios. Depending on the objective of optimisation, these studies are classified into two types, namely maximising the coverage (Chauhan, Unnikrishnan, & Figliozzi, 2019; Pulver, Wei, & Mann, 2016; Pulver & Wei, 2018) and minimising the service cost (including monetary cost, time, distance, and energy) (Chowdhury, Emelogu, Marufuzzaman, Nurre, & Bian, 2017; Dukkanci, Kara, & Bektaş, 2021; Feng, Murray, & Church, 2021; Feng & Murray, 2020; Ghelichi, Gentili, & Mirchandani, 2022; Leung et al., 2022; Lynskey, Thar, Oo, & Hong, 2019; Zhu, Boyles, & Unnikrishnan, 2022). More details about these studies are presented in Table 1.

There are two fundamental challenges that affect drone deployment in urban areas, including determining flight routes and accurately measuring travel impedance between drone stations and demand points. Most studies assume drones fly in straight lines, using Euclidean distance as a measure. However, the actual flying routes of drones are more complex due to factors like buildings, uneven terrains, and non-fly zones imposed by regulations (Pulver & Wei, 2018). Relying solely on the simplified Euclidean distance can lead to inaccurate estimations of flying time and ineffective drone deployment. Therefore, it is essential to evaluate and compare different distance settings for drones when selecting the locations of drone base stations. This study focuses on addressing these aspects, considering the varying distance measures and their impact on the effectiveness of drone station location selection.

Table 1
Details of related research on the location selection of drone sites.

Refs.	Application	Distance metric	Objective	Considerations
Pulver et al. (2016)	AED-equipped drones for cardiac arrest response	Euclidean	To maximise service coverage of the cardiac arrest	Travel time and implementation costs
Pulver and Wei (2018)	AED-equipped drones for cardiac arrest response	Euclidean	To maximise the primary and backup coverage of the cardiac arrest	Backup coverage and distributed demand
Chauhan et al. (2019)	Delivery	Euclidean	To maximise the service coverage	Drone energy consumption and range constraints
Chowdhury et al. (2017)	Delivering emergency supplies to disaster-affected areas	Euclidean	To minimise the overall cost	Facility cost and transportation cost
Lynskey et al. (2019)	Visiting locations and taking photos	Euclidean	To minimise the average distance of drone delivery	Drone port locations and energy cost
Dukkanci et al. (2021)	Delivery	Euclidean	To minimise the total operational cost (incl. energy consumption)	Drone speed, energy consumption, and the drone range
Feng, Murray, and Church (2021)	AED-equipped drones for cardiac arrest response	Euclidean	To minimise the average distance of service	The effect of wind speed on drone flying costs; spatio-temporally varying demand
Zhu et al. (2022)	Delivery of first-aid products post-disaster	Euclidean	To minimise the total fixed facility cost and the worst-case operational cost	Demand uncertainty; energy consumption models of drones
Leung et al. (2022)	AED-equipped drones for cardiac arrest response	Euclidean	To minimise the overall response time	Different drone base locations and travel time
Ghelichi et al. (2022)	Delivery of humanitarian aid packages	Euclidean	To minimise the maximum total cost across possible scenarios	Multiple demand scenarios; demand with uncertainty

3. Methods

3.1. Framework

This section proposes a new risk-based decision framework that enables the optimisation of police drone services for crime incident response on urban street networks and rationalising police drone location selection, as shown in Fig. 1. In Step 1, the street-level crime risk is estimated from the historical crime incidents using a street network Kernel Density Estimation (KDE). In Step 2, the settings of drone services are determined by police officers with experience in patrol, emergency response, and local crimes. These settings include determining the number of drones and potential sites of drone base stations. In Step 3, the optimal location of drone base stations is determined by comparing different distance metrics that influence the flying routes and services of police drones. If the distance metrics lead to different configurations of drone base stations, the most feasible configuration will be selected via detailed comparison and analysis.

It is noteworthy that this paper takes into account crime risk and police drone deployment on street segments rather than on grid cells or administrative regions. This street network-based approach is consistent with an increasing body of research that investigates crime and policing at the street level (Chen & Cheng, 2017; Chen, Cheng, & Shawe-Taylor, 2018; Rosser, Davies, Bowers, Johnson, & Cheng, 2017; Weisburd, Groff, & Yang, 2012). There are several reasons why network-based models are appropriate for describing and predicting crime patterns. First, routine activity theory (Cohen & Felson, 1979) suggests that direct contact predatory crimes happen as a result of human interaction that emerges as a result of routine activities; crime pattern theory (Brantingham & Brantingham, 1993) suggests that the mobility patterns of offenders, victims, and guardians in routine activities lead to the development of activity spaces and pattern of crimes. Since a significant amount of urban crime and policing activity occurs on or along streets, street segments represent a meaningful spatial unit for predicting crime

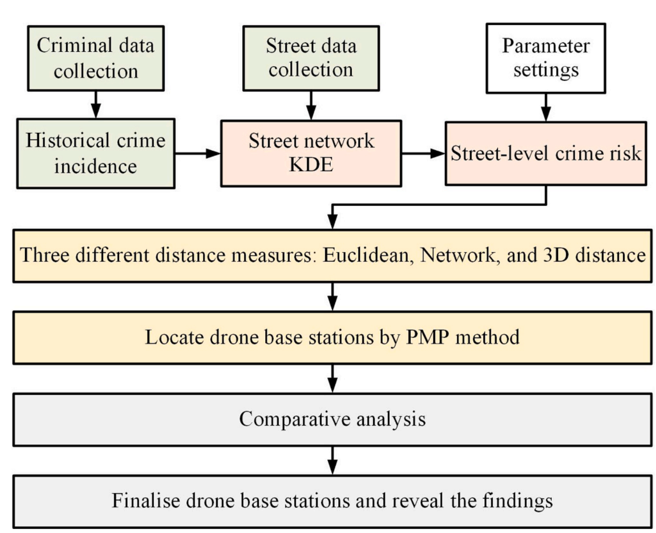

Fig. 1. The framework for optimising police drone services in urban areas.

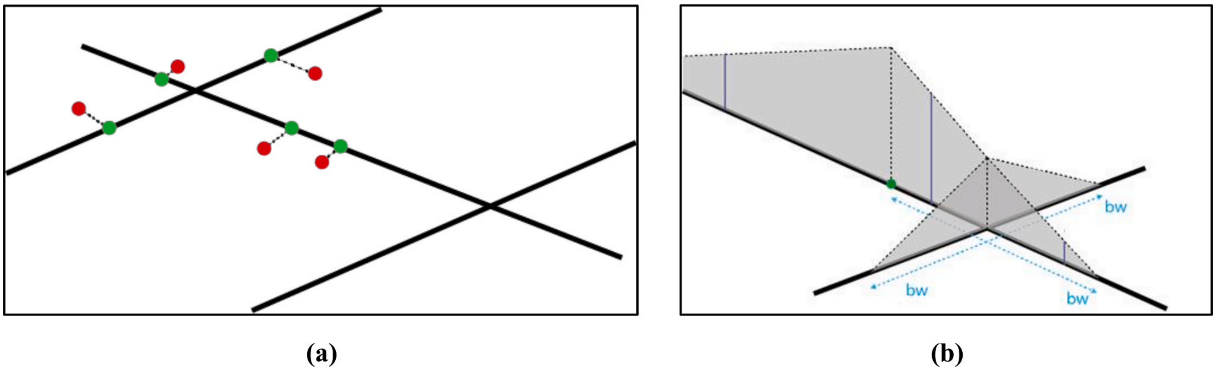

Fig. 2. Illustration of network KDE (Gelb, 2022). (a) Events (red dots) snapped to the network (green dots); (b) the kernel function of a snapped event and the density distribution.

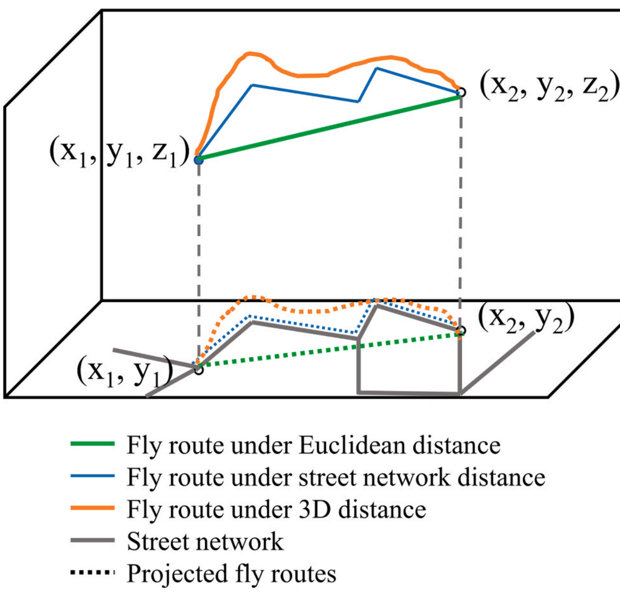

Fig. 3. Illustration of the drone fly routes under three distance metrics: Euclidean distance (green), street network distance (blue), and 3D distance (orange). On the bottom surface, the grey lines represent a street network, and dotted lines represent the corresponding projected routes. This figure is motivated by (Feng, Murray, & Church, 2021).

risk and reducing crime. Second, the features of the street network are likely to influence the long-term level of crime risk (Davies & Johnson, 2015) and the short-term dynamics of crime risk (Johnson & Bowers, 2014).

3.2. P-median problem

This section describes the p-median problem (PMP) for the location selection of drone base stations. PMP was proposed to optimise the locations of p facilities so that the total weighted travel distance to the given demands is minimised (Hakimi, 1964). It assumes that each demand would be serviced by the nearest facility site that is selected by PMP. In this study, demands refer to street segments, with their demand weight representing the predicted crime risk, while facilities pertain to police drone base stations. To introduce PMP in police drone potrolling, the following notations are used.

i: index of demand units, $i = 1, \ldots, n$

a_i: demand size at i.

j: index of potential facility sites, $j = 1, \ldots, m$

d_{ij}: the shortest distance or travel time from demand unit i to potential facility site j

p: number of facilities to locate.

$$x_j = \begin{cases} 1, & \text{if a facility is sited at location } j \\ 0, & \text{otherwise;} \end{cases}$$

$$z_{ij} = \begin{cases} 1, & \text{if demand } i \text{ is assigned to facility } j \\ 0, & \text{otherwise;} \end{cases}.$$

With this notation, the PMP is formulated as follows:

$$Minimise \sum_{i,j} a_i d_{ij} z_{ij} \tag{1}$$

Subject to:

$$z_{ij} \leq x_j, \ \forall i,j \tag{2}$$

$$\sum_j x_j = p \tag{3}$$

$$\sum_j z_{ij} = 1, \ \forall i \tag{4}$$

$$x_j \in \{0,1\}, \ \forall j \tag{5}$$

$$z_{ij} \in \{0,1\}, \ \forall i,j \tag{6}$$

In the context of this study, the PMP objective (1) is to minimise the total weighted distance between all street segments and drone base stations, using the estimated street-level crime level as weights. Constraint (2) implies that a street segment can be serviced by drones from a base station at location j only if there is a station located at j. Constraint (3) ensures that the p drone stations are located. Constraint (4) indicates that each street segment should be serviced by one drone station. Finally, constraints (5) and (6) impose binary restrictions on decision variables, including whether a location j is selected to set up a drone base station and whether a street segment i is serviced by a drone station at location j.

3.3. Street network Kernel density estimation of crime risk

The crime risk of each street segment is estimated using historical crime points data and street network KDE. A classical KDE estimates the density of a set of point events in a two-dimensional space that was divided into grid cells. It is, however, improper to analyse the density of events in a network for two reasons. First, the network is not an isotropic space, and movements in a network are only along the edges of the network. Second, estimating the density of locations outside the network is meaningless. Network KDE has been proposed to address these issues and provide an accurate estimation of density on the edges of a network (Gelb, 2022). The workflow of Network KDE is illustrated in Fig. 2, which consists of two steps. First, an event is snapped to the nearest

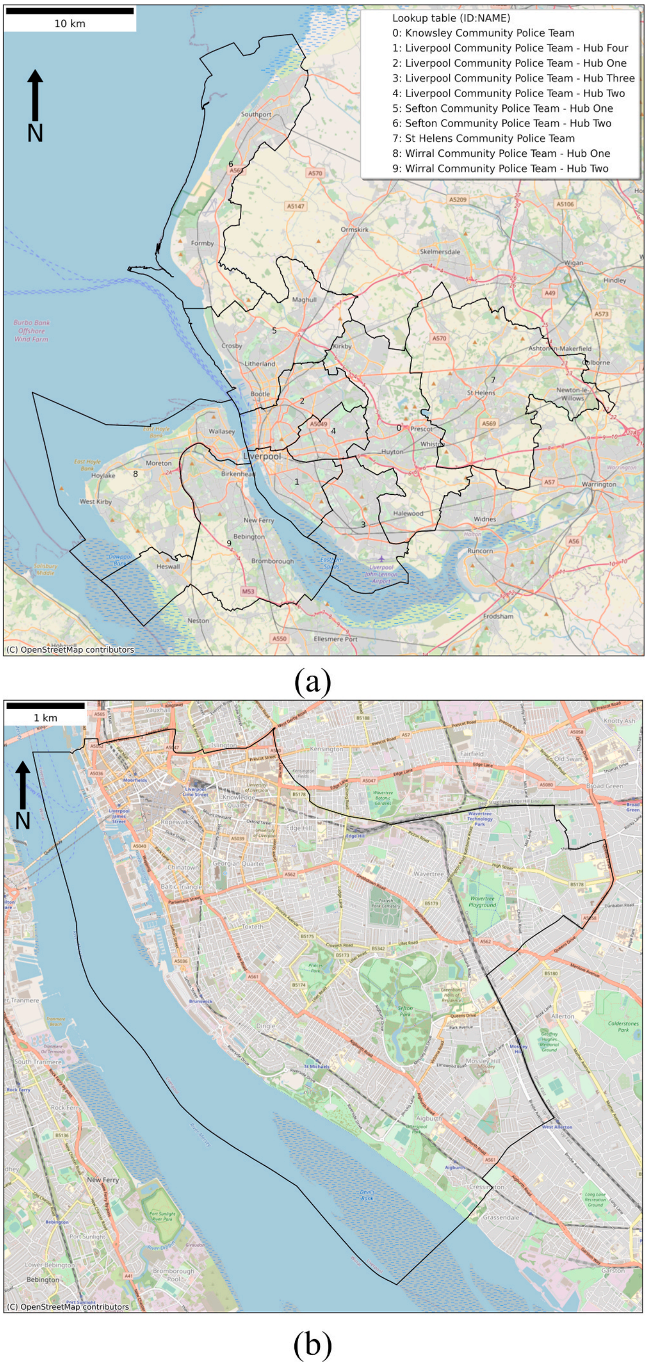

Fig. 4. The map of the case study. (a) Merseyside (consisting of 10 police neighbourhoods); (b) the neighbourhood of Liverpool Community Police Team Hub Four.

Table 2
The list of POI types selected to equip the drones.

POI code from OS	POI type	Number of sites
422	Police Stations	2
414	Fire Brigade Stations	1
106	Medical Equipment Rental and Leasing	3
356	Ambulance and Medical Transportation Services	2
293	Gymnasiums, Sports Halls and Leisure Centres	48
456	Halls and Community Centres	37

street segment of a network if it does not fall on any street of the network. Second, the risk imposed by each event is represented by a kernel function, which decays along the network and is divided at each intersection (see Fig. 2(b)). In this study, the network KDE is implemented using the "spNetwork" (Gelb, 2021) in the R environment (R Core Team, 2015). The kernel function used is a quadratic function, and the bandwidth is set as 300 m, as most police drones would fly 300 m in 20 s, which is a reasonable response time for police to a crime incident.

3.4. Distance metrics

Three types of distance metrics are taken into account in this study due to their potential impact on police drone patrolling in reality. In other words, distance metrics might affect the flying routes and response time of police drones (see Fig. 3) according to the characteristics and regulations of the area. Under each metric, the shortest route of drones is adopted. The first one is an Euclidean distance (or straight-line distance), which is used as the baseline in this study. This metric is simple to compute and has been used in many studies that optimise the location of medical drone stations (e.g. Pulver & Wei, 2018; also see Table 1). The second metric is calculated by street network distance, which regulates that drones only fly over public street networks and are not permitted to fly over buildings, especially critical infrastructures (e.g. government buildings and military ranges). This metric is tested due to the concerns of potential damages of drones to facilities or any privacy issues caused by flying drones. The third distance metric is a 3D distance, which mirrors the fact that drones maintain a consistent vertical distance from the ground by adjusting their altitude in response to the terrain, ensuring that they remain at a uniform height above the ground even when encountering slopes. This metric is reasonable as the Civil Aviation Authority (CAA) requires drones to fly below the legal height limit of 120 m (Civil Aviation Authority, 2022). Moreover, drones with a sufficient vertical distance from the ground would avoid collision risk to buildings or hills.

4. Case study

In this section, the Liverpool city region, as part of Merseyside in North West England, is taken as the case study area due to its unique and mixed geographical characteristics. Furthermore, Merseyside Police, the police force responsible for Merseyside, has been a pioneer in the UK in launching a police drone unit in practice (BBC, 2010). Merseyside Police, currently serving a population of 1.5 million and covering an area of 647 km^2, is divided into five local policing teams (i.e. Wirral, Sefton, Knowsley, St Helens, and Liverpool) and further into 10 neighbourhoods. Among them, the neighbourhood of *Liverpool Community Police Team - Hub Four* (called Liverpool Hub Four for short) is selected as the case study area, as it has a higher crime rate than the other neighbourhoods and is in the city centre of Liverpool. In 2021, there were 978 crime incidents per square kilometre (km^2) in Liverpool Hub Four, compared to the second highest of 828 incidents/km^2 in Liverpool Hub Two and the lowest of 105 incidents/km^2 in Wirral Hub One. Fig. 4 presents the 10 neighbourhoods in Merseyside and then zooms into the Liverpool Hub Four. Notably, the northern section of Liverpool Hub Four contains a higher density of major roads compared to other areas, potentially resulting in increased network distances within this section.

Several open datasets were obtained and used in this study. The aggregated crime incident data for the year 2021 were retrieved from Police UK (Police UK, 2022), in which crime incidents are spatially aggregated to the central points of streets. In total, 29,000 crime incidents were found in this region, which consists of a wide range of crimes, including anti-social behaviour, bicycle theft, burglary, criminal damage arson, drugs, other theft, possession of weapons, public order, robbery, shoplifting, theft from the person, vehicle crime, violent crime, and other crime. These crime types are selected as police drones can be used to search and locate the fleeing suspects and gather evidence when

Fig. 5. The estimated street-level crime risk in the Liverpool city region.

Table 3
Summary of the PMPs in this case study.

Distance metric	Number of demand points	Number of potential sites	Computing time (seconds)	Average facility-demand distance
Euclidean	1710	93	33.5	623.3
3D	1710	93	56.5	658.2
Network	1710	93	15.7	836.9

these crime incidents take place, leading to effective crime detection. The street network was obtained via OpenStreetMap. The Point-Of-Interest (POI) data was sourced from the UK Ordnance Survey (OS) and Digimap and was used to define potential drone sites. We chose six POI types to equip the drones, which led to a total of 93 POI sites (see Table 2). In addition, the Digital Terrain Model (DTM) data (originally with a spatial resolution of 2 m) was acquired and resampled into a 20-m resolution before being used to compute the 3D distance (Department for Environment Food & Rural Affairs, 2022). This DTM product is called LIDAR Composite DTM and was collected and produced in 2020.

Several settings are assumed to define the types and permissions of the drones used by Merseyside police without loss of generalisation. First, the police stations have acquired CAA permissions to fly drones legally. Second, these drones are below 500 g and C0 or C1 class so that they can fly closer to people than 50 m (Civil Aviation Authority, 2022). It is important as drones are likely to fly across busy urban areas. Third, the drones are equipped with batteries that can support flying from a base station to incident sites, and no charging is needed in the flying route. This requires elaborate planning of service zones of base stations and drones. The PMP instances are implemented using the “spopt” (Feng, Gaboardi, Knaap, Rey, & Wei, 2021) in Python and are optimally solved by Gurobi Optimization (2016), a commercial solver for mixed programming problems. The case study was conducted on a Linux Ubuntu server with Intel(R) Xeon(R) CPU E5-2630 v4 (2.20 GHz) and

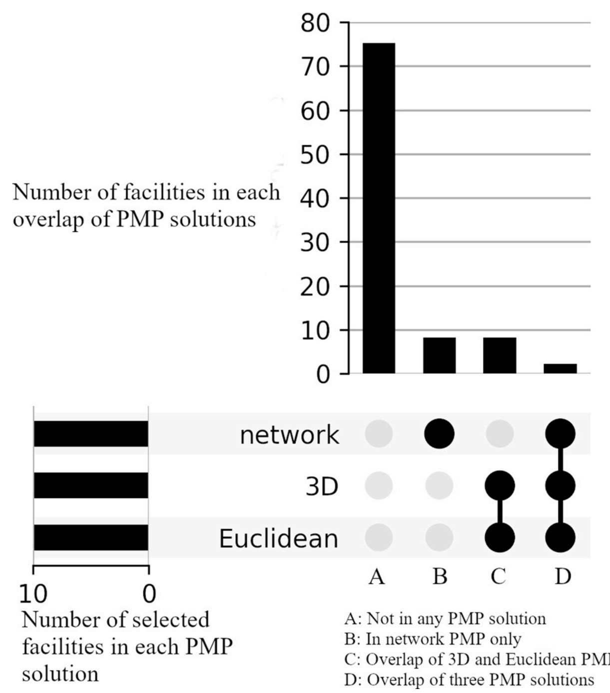

Fig. 6. Overlap of the optimal facilities derived from three PMPs.

251 GB RAM.

5. Results and discussion

5.1. Estimated crime risk on the street network

The street-level crime risk is estimated based on the historical crime

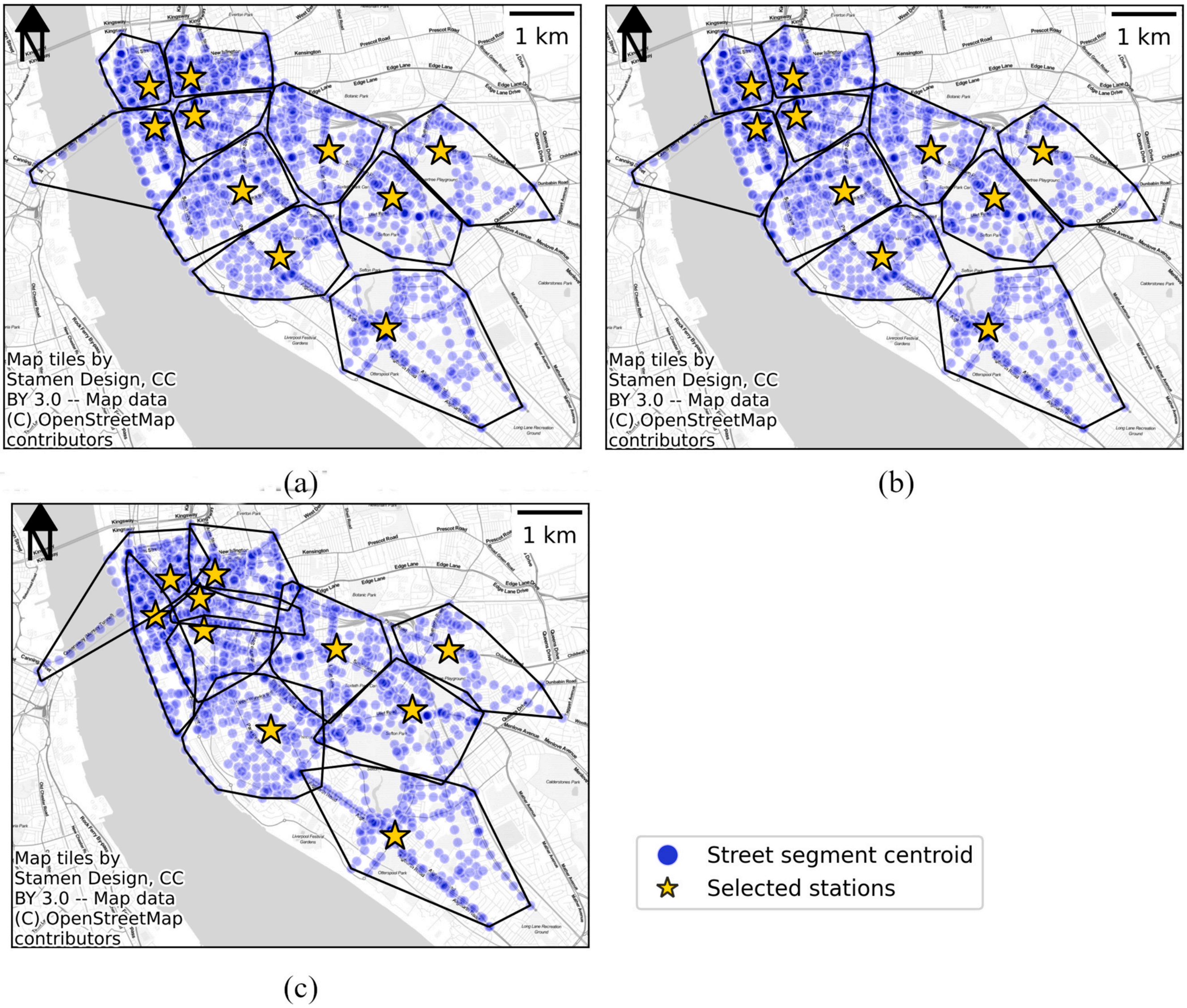

Fig. 7. PMP-derived configuration of drone bases for serving the Liverpool Hub Four neighbourhood under different distances. (a) Euclidean; (b) 3D; (c) street network.

incidents and the Network KDE algorithm, and the risk level of street segments is demonstrated in Fig. 5. The segment of darker red means a higher crime risk on the street. The map shows that the northern part has a higher street density and a higher crime risk than other areas. Therefore, it is expected that more drone stations should be set up in this area to provide quick responses to potential crime incidents.

5.2. PMP results

The results of the three PMP instances are detailed in Table 3. The solution time for all PMP instances is less than 60 s, which demonstrates the efficiency of the proposed models. The average demand-facility distance indicates the average distance from each street segment to its assigned facility site. The average Euclidean distance is considerably shorter than the network distance, which is reasonable as the street network generally adds to the travelling distance between locations in urban areas.

The three PMP instances led to different optimal configurations of drone stations. The overlaps of the selected locations are illustrated by the upset plot in Fig. 6. The three rows of this matrix correspond to the sets of facilities (i.e. facilities derived from Euclidean, 3D, and network-PMP), while the columns correspond to the cardinality of overlap between the given sets. Column A indicates that 75 out of 93 potential sites are not selected by any PMP. The last column represents the intersection between the facilities selected by all three PMP instances, meaning that the three instances have only two selected facilities in common. In addition, the third and fourth columns express that the Euclidean and 3D PMP derived identical optimal facilities.

The optimal spatial configurations of the facilities are shown in maps in Fig. 7. In each map, a polygon represents the convex hull of the streets that are assigned to each selected facility (which is also inside the polygon). When the Euclidean or 3D distance is applied, the facilities derived from the PMP and the streets assigned to the selected facilities are the same. This is potentially because the landscape of the Liverpool city centre is quite flat (the DTM data with a median of 27.0 m, mean of 26.1 m, and a maximum of 92.5 m), leading to a similar Euclidean and 3D distance. On the other hand, the facilities derived from the street network distance are distinctively different from the Euclidean distance, with more facilities located in the northwest part of this area. This can be explained by the fact that this subarea intersects with the River Mersey and several dual carriageways, leading to a substantially longer distance on the network than in an Euclidean space. For this reason, the network PMP tends to set up more drone sites in the northwest part.

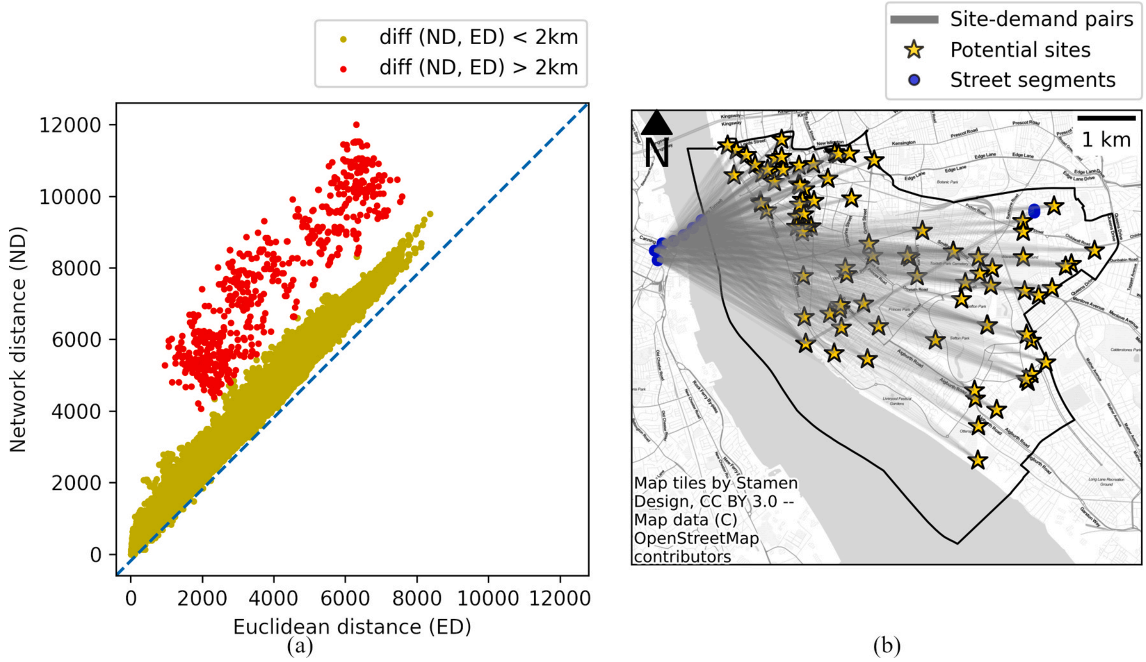

Fig. 8. The comparison of the street network and Euclidean distances per demand-facility pair. (a) Scatter plot of all demand-facility pairs, highlighting the pairs with a distance difference above 2 km; (b) Map of the demand-facility pair with a distance difference above 2 km.

5.3. Spatial analysis of differences between distance metrics

In this part, a series of spatial analyses are conducted to understand the main differences among the three distance metrics, elucidating the reasons behind the different optimal facilities selected by the PMP models. Fig. 8(a) depicts the comparison of the street network and Euclidean distances for each demand-facility pair. It is observed that 619 demand-facility pairs out of 159,030 (0.389%) have a significant difference greater than 2 km between the two distances. These points are highlighted in red in Fig. 8(a) and then illustrated in the map of Fig. 8(b). This spatial pattern shows that these outlier distances relate to the street links on the Queensway Tunnel and in the eastern part of this area, probably because of the intersections of dual carriageways and River Mersey. This result is consistent with the configuration of drone stations chosen by the network PMP, where five stations are selected to cover the street segments in the northern part, compared to the counterpart of four stations selected by the Euclidean PMP. These findings confirm the influence of distance metrics on the optimal locations of drone stations.

5.4. Discussion and implications

The analysis above presents three configurations for the optimal locations of police drone stations, which are derived from three distance metrics. We demonstrate that the configuration derived from the network distance is more practicable and efficient because of several considerations. First, compared with Euclidean and 3D distance metrics, this network PMP sets up more drone stations in the northern part that feature a higher density of street segments and a higher crime risk, which likely leads to a quicker response to crime incidents in this area. Second, if police drones mostly fly over streets rather than buildings (including critical infrastructures), it would considerably reduce the potential damage of drones to buildings and reduce the public's concerns about drones with respect to safety, security, and privacy.

This study provides theoretical implications on how to incorporate risks into drone applications in a wide range of sectors, including military, medical, firefighting, and high-risk manufacturing (e.g. nuclear and chemical plants), to improve the efficiency of drone operations. Furthermore, it provides a basis for future studies on risk-based drone routing and scheduling, in which more constraints, such as the limited flight range of drones, will be considered. From a managerial perspective, the framework in this study can effectively improve police patrolling efficiency by minimising the total travel distance of drones (hence cost and response time) and maximising public security and welfare.

This research highlights the importance of optimising the base station locations of police drones, which leads to multiple benefits for law enforcement agencies. Firstly, it allows for maximised coverage, ensuring that drone services can reach a larger area and monitor a greater number of street segments. This extended coverage enhances the ability to detect and respond to incidents promptly. Secondly, optimal base station locations would minimise the response times of the police to crime incidents or high-risk areas. This rapid response capability enables law enforcement agencies to gather real-time situational awareness, which supports timely decision-making. Additionally, the optimal drone base station locations contribute to efficient resource allocation, as it allows law enforcement agencies to prioritise areas with greater need for surveillance and crime detection.

It is significant to integrate the selection of drone base station locations into the overall planning and deployment of police drones, as it has important implications for crime detection, surveillance, and emergency response. This comprehensive approach takes into account both the spatial aspects and the operational requirements of police drones. Through this integration, law enforcement agencies can optimise their resources, improve public safety outcomes, and enhance their capabilities in addressing and combating crime. In summary, the selection of optimal drone base station locations has implications for maximising coverage, minimising response times, and ensuring efficient resource allocation of police drones. By integrating this selection process into the overall planning and deployment strategy, the effectiveness of crime detection, surveillance, and emergency response is enhanced, leading to improved public safety outcomes.

5.5. Limitations

This study has several limitations, which open the avenue for future research. First, the drones are assumed to follow the shortest route under the given distance metric. However, in real applications, the flying of drones is affected by other factors, including no-fly zones, weather conditions, and high buildings. Future work will take into account these factors in the route planning of drones and engage police experts in the ranking of these important factors. Second, this research assumes fixed and static police drone stations once they are located and set up. However, future work could accommodate the docking and charging of drones via dynamic vehicle-based drone stations. Moreover, this work assumes that the crime risk is only dependent on the frequency of crime incidents. Future work will incorporate the severity level of each incident to improve risk-based drone patrolling.

6. Conclusions

In this study, we present a new risk-based decision framework for the optimal deployment of police drones for responding to crimes on urban street networks based on historical crime data, crime risk levels, network KDE, and PMP. Specifically, we adopt the spatial optimisation model to derive the optimal configuration of drone stations, considering different distance metrics that affect the flying routes of drones. This framework is implemented and tested in the case study of Liverpool city. Given the three configurations of drone station locations, we illustrate that the configuration derived from the network distance is more practicable and efficient than the others. The results have important policy implications for the deployment of police drones and for reducing the risk in urban areas.

This study initiates a theoretical exploration of risk-based deployment of police drones for patrolling and seeks the optimal locations of drone base stations using spatial optimisation models. The objective is to ensure the coverage of street segments in urban environments, where each segment is assigned a crime risk level based on historical crime records.

This study makes several significant contributions to the existing literature on drone base station location selection. First, it introduces the concept of risk-based drone patrolling by pioneering the incorporation of street-level crime incident data into drone location optimisation. The innovative approach considers crime risk levels derived from historical records, providing a new perspective on improving the effectiveness of police drone operations. Second, the study formulates and solves the drone station location selection problem. It presents a new formulation specifically tailored to selecting drone base station locations police patrolling. Through the development spatial optimisation models, the research addresses the practical aspects of drone deployment in law enforcement, contributing to applied research in this domain. In addition, this study extends the boundaries of police patrol practices by discussing the utilisation of drones for police patrolling. This extension provides valuable insights for future operations and management of police drones in urban areas, potentially influencing the direction of law enforcement practices.

CRediT authorship contribution statement

Huanfa Chen: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing, Conceptualization. **Xiaowei Gao:** Data curation, Formal analysis, Investigation, Validation. **Huanhuan Li:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Project administration. **Zaili Yang:** Conceptualization, Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors report there are no competing interests to declare.

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