Design of Smart City Considering Carbon Emissions under The Background of Industry 5.0

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Abstract

Industry 5.0 puts forward higher requirements for smart cities, including low-carbon, sustainable, and people-oriented, which pose challenges to the design of smart cities. In response to the above challenges, this study introduces the cyber-physical-social system (CPSS) and parallel system theory into the design of smart cities, and constructs a smart city framework based on parallel system theory. On this basis, in order to enhance the security of smart cities, a sustainable patrol subsystem for smart cities has been established. The intelligent patrol system uses a drone platform, and the trajectory planning of the drone is a key problem that needs to be solved. Therefore, a mathematical model was established that considers various objectives, including minimizing carbon emissions, minimizing noise impact, and maximizing coverage area, while also taking into account the flight performance constraints of drones. In addition, an improved metaheuristic algorithm based on ant colony optimization (ACO) algorithm was designed for trajectory planning of patrol drones. Finally, a digital environmental map was established based on real urban scenes and simulation experiments were conducted. The results show that compared with the other three metaheuristic algorithms, the algorithm designed in this study has the best performance.

Keywords: Smart City; Cyber-Physical-Social Systems; Smart Patrol Platform; Drone Trajectory Planning; Ant Colony Optimization Algorithm

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1. Introduction

With the development of cutting-edge technologies in the field of artificial intelligence such as the Internet of Things (IoT), CPSS, and 6G communication, hardware foundations have been provided for the implementation of smart cities [1]. The design goal of a smart city is to improve the service quality of the city through digital technology, big data, and advanced communication technology. Industry 5.0, as a promising direction for disruptive technology, integrates physical cities, cyber cities, and social cities into the design process of smart cities, emphasizing more on the safety, sustainability, and people-oriented aspects of smart cities [2]-[3]. How to integrate the enabling technologies of Industry 5.0 with smart cities and introduce cutting-edge technologies such as CPSS, drones, and metaheuristic algorithms into the design of smart cities has always been a challenge that needs to be faced in the process of smart city design [4].

To address the above challenges, researchers have started using a paradigm of integrating one or several technologies from Industry 5.0 and successfully applying the integrated technology to a subsystem of a smart city [5]. Industry 5.0 not only focuses on the level of intelligence in smart cities, but also pays more attention to the sustainability and people-oriented of smart cities. Specifically, in the context of Industry 5.0, smart cities should pay more attention to environmental protection, human physical and mental health [6]. Therefore, this paradigm is typically driven by Industry 5.0, with the goals of sustainability, low-carbon, safety, and people-oriented. However, there is currently no research that provides a strict definition for this paradigm. Therefore, this study attempts to introduce parallel system theory and CPSS into the process of smart city design, defining the smart city design paradigm driven by Industry 5.0.

The parallel system theory is a paradigm proposed by Dr. Wang for managing large-scale complex systems. The parallel system theory uses ACP as a tool and CPSS as a method to control and manage large-scale complex systems through virtual real interaction and parallel operation [7]-[8]. Smart cities, as a typical large-scale complex system, are a promising carrier for applying parallel system theory and CPSS. It can be foreseen that the operation process of future smart cities will inevitably rely on modeling and solving based on large-scale complex systems. Meanwhile, an enabling technology for Industry 5.0 is cyber-physical systems and the modeling of the entire system. Therefore, it is feasible to define a smart city design paradigm driven by Industry 5.0 based on the theory of parallel systems and CPSS.

In addition, the smart patrol system in smart cities can collect and analyze various data in real time, timely detect safety hazards and abnormal situations, which is of great significance for improving the safety level of cities and promoting sustainable development [9]. Drone-based intelligent patrol is a comprehensive monitoring of urban facilities, transportation, and environment through the use of drones, and indicative examples include drone-based environmental monitoring [5], and drone-based road detection [10]. During specific patrols, drones equipped with various sensors can collect and analyze relevant data of the city, providing decision support for city managers, thus improving the quality of the urban environment and the quality of life of residents. Therefore, Section 4 of this study focuses on exploring the modeling and solution methods of security patrol systems applied to smart cities.

Unlike previous studies, this study focuses more on the impact of Industry 5.0 on smart cities. Therefore, it can be determined that the purpose of this study is to construct a smart city framework based on parallel system theory and CPSS in the context of Industry 5.0, with a focus on drone-based patrol systems for urban safety. The main contributions of this study are summarized as follows:

(1) This study is based on the theory of parallel systems and for the first time introduces CPSS into the construction of smart cities. A smart city modeling method was proposed to map the real physical social world to the cyberspace.

(2) A subsystem for smart city patrol has been built, and a mathematical model for drone trajectory planning for smart city patrol tasks has been established. This model considers multiple objectives such as minimum carbon emissions, minimum noise impact, and maximum coverage area, aiming to complete smart city patrol tasks through drones.

(3) Based on the ACO algorithm and differential evolution (DE) algorithm, an improved metaheuristic algorithm, the differential evolution-based ant colony optimization (DE-ACO) algorithm, was developed to solve the mathematical model of drone trajectory planning for patrol tasks.

(4) A digital environment model was established through real urban scenes, and simulation experiments were conducted. The results showed that compared with the improved group search optimization (IGSO) algorithm, the improved ACO (IACO) algorithm, and the DE algorithm, the DE-ACO algorithm designed in this study had the best performance.

The other parts of this study are as follows, Section 2 reviews the literature related to this study. Section 3 proposes a smart city design paradigm based on parallel systems theory. Section 4 establishes a drone-based patrol system for smart cities. Finally, Section 5 concludes the full study.

2. Literatures Review

How to make the "sustainable", “resilient" and "human-centered" goals of Industry 5.0 be reflected in the design process of smart cities has been a key concern of researchers [5]. In research related to smart cities, including streetlight systems [11], emergency communication systems [12], transportation systems [13], energy systems [14], and power grid systems [15], all of these subsystems are aimed at maximizing system efficiency, minimizing system operating costs, and minimizing system carbon emissions. Industry 5.0 does not only impose requirements on sustainability and cybersecurity, but its requirements on the impact of automated devices on humans as well [16]. Therefore, the purpose of smart city design in the context of Industry 5.0 can be identified, which mainly includes increasing the favorable impacts on human society, such as increasing efficiency and decreasing production costs; and at the same time, decreasing the unfavorable impacts on human society, such as invasion of personal privacy and noise pollution on human society [17].

Meanwhile, relevant researchers have established a large number of subsystems for smart cities based on CPSS. Liu et al. established a parallel trajectory planning system based on CPSS for grid patrol tasks in smart cities [16]. Amin et al. designed a hotspot analysis framework based on CPSS for the upgrade process of telecommunications equipment in smart cities [18]. Roy et al. proposed a transportation system based on CPSS [19]. Pasandideh et al. also summarized a series of potential application scenarios of CPSS in smart city scenarios and proposed the challenges of applying CPSS to smart cities [20]. It is worth noting that the above studies have actively explored the application of CPSS in smart city scenarios, but have not proposed a universal paradigm for smart city design in the context of Industry 5.0.

The works [15] and [19] aim to eliminate the negative impacts of automated technologies on human society from a cybersecurity perspective. However how to enhance the security of the smart city itself has not received much attention. An automated patrol system for smart city scenarios, on the other hand, can directly enhance the safety of the city and the city's ability to resist natural disasters. Patrol systems used in smart cities can not only provide services for emergencies such as car accidents, but also it can play a role in the emergency rescue process after a disaster [21]. The Internet of Things (IoT) technology [22]-[23], drones [24]-[25], and high-precision sensors [26] provide the hardware foundation for smart patrol systems. Before conducting patrols, the offline trajectory planner needs to first plan a global trajectory for the drone based on its patrol range, three-dimensional environment, and relevant parameters [27]. A large number of existing robot trajectory planning schemes [28]-[29] and heuristic algorithms [30]-[31] have provided possibilities for the establishment of drone-based patrol systems in smart cities.

Unlike the traditional heuristic algorithms used in work [30], meta heuristic algorithms have the advantages of simple structure, fast convergence speed, and the ability to handle large-scale optimization problems. Therefore, in the process of robot path planning, a large number of metaheuristic algorithms are used. Li et al. developed an improved ACO (IACO) algorithm to address the problem of the ACO algorithm easily falling into local optima during the search process, and successfully applied it to the trajectory planning problem of unmanned aerial vehicles [32]. Reference [33] designed a mathematical model for UAV trajectory planning considering multiple objectives, and also improved the ACO algorithm to solve UAV trajectory planning problems. Reference [34] applies the differential evolution (DE) algorithm to the trajectory planning problem of storage drones. Taha et al. also used an improved DE algorithm when solving robot paths [35]. Works [24] and [36] designed an improved group search optimization algorithm (IGSO) for solving unmanned aerial vehicle trajectory planning problems in three-dimensional environments.

3. Framework of Smart City Driven by Industry 5.0

3.1 The Basic Framework of Parallel Cities

The smart city based on parallel system theory is a typical urban model under the background of Industry 5.0 [3]. However, introducing cutting-edge technologies including CPSS, drones, and metaheuristic algorithms into the design of smart cities has always been seen as a challenge. Meanwhile, the impact of human activities in smart cities is also an issue that cannot be ignored. Therefore, this section focuses on the basic framework of people-oriented parallel cities.

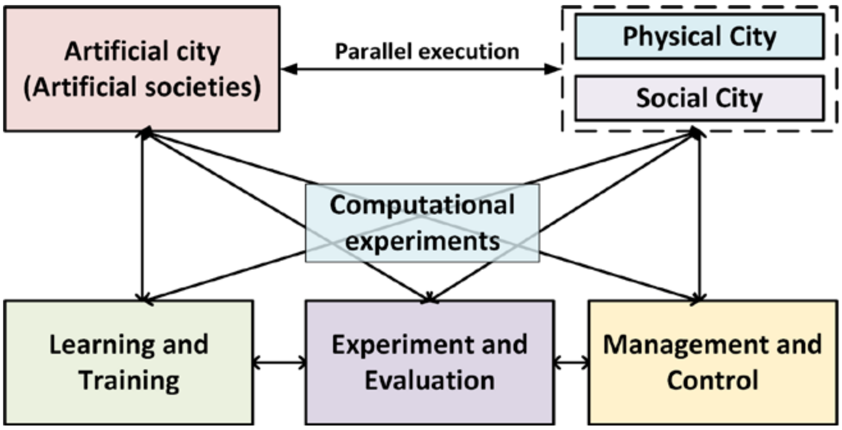

Fig. 1. The basic framework of parallel city.

Fig. 1 shows the basic framework of parallel cities, which are composed of physical cities, social cities, and artificial cities. Artificial cities are the reproduction of the real world in the online world, mainly composed of model libraries, algorithm libraries, and software humans. This framework mainly includes three main steps: learning and training, experimentation and evaluation, and control and management.

3.2 Computational Experimental Framework for Smart Cities CPSS-based

Based on the various subsystems built based on CPSS for smart cities in the works [16]-[20], a CPSS-based smart city framework was designed and **Fig. 2** shows the computational experimental framework for a CPSS-based smart city designed in this research.

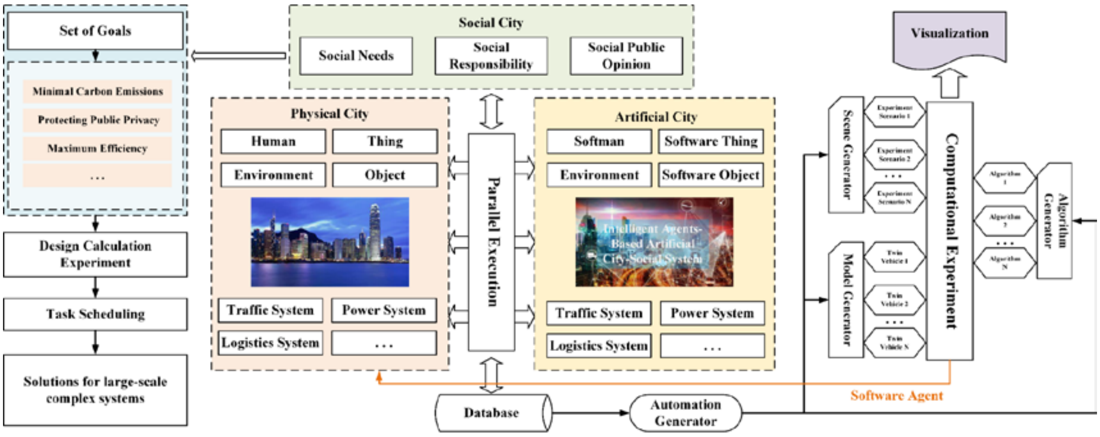

Fig. 2. The computational experimental framework for smart cities CPSS-based.

3.2.1 The Goals of Smart Cities CPSS-based

As previously summarized, the purpose of smart city design in the context of Industry 5.0 can be determined to enhance its beneficial impact on human society while reducing its adverse effects [16]-[17]. As shown in **Fig. 2**, these goals are generated based on social cities, and all goals are identified as a set of goals that need to be considered in the design process of smart cities. According to existing research, the design goals of smart cities in the context of Industry 5.0 can be preliminarily summarized as low-carbon, efficient, safe, and society-oriented.

3.2.2 The Operation Process of Smart Cities CPSS-based

Step 1: Establish corresponding objective functions based on the actual needs of logistics systems, transportation systems, and energy systems in the context of smart city scenarios, combined with the development demands of human society. By adopting CPSS and other means, the environment, maps, and tools in real cities are mapped to the online world, forming a digital environment, digital maps, and software tools, and constructing a cyber city corresponding to real cities.

Step 2: Based on the data collected by sensors in real cities, including user needs, computational experiments are conducted using databases in artificial cities. Specifically, after the subsystem obtains the user requirements in the real world, based on digital models such as environmental models, relevant algorithms in the algorithm library are mobilized, and finally relevant solutions are provided.

Step 3: The interconnection between virtual cities and real cities is achieved through communication devices such as base stations and wireless networks, thereby achieving virtual and real interaction between the two systems and parallel execution. Finally, complete the management and service of the entire city.

4. Intelligent Patrol System for Smart Cities

In this section, a patrol subsystem was established based on the goal of smart city design in the context of Industry 5.0. According to the smart city framework built in Section 3, a case study of a patrol subsystem for smart cities is presented. Unlike traditional manual patrol methods, in order to reduce carbon emissions, the patrol subsystem uses drones for patrols. According to works [2]-[6], Industry 5.0 not only focuses on the level of intelligence in smart cities, but also pays more attention to the sustainability and people-oriented nature of smart cities. In the context of Industry 5.0, smart city design should pay more attention to environmental protection, human physical and mental health. Therefore, the mathematical model of the UAV-based patrol subsystem designed by this research institute mainly considers carbon emissions, patrol efficiency, and noise pollution. Among them, the maximum patrol efficiency meets the efficiency requirements of Industry 5.0. Minimizing carbon emissions and minimizing noise pollution meet the environmental and people-oriented requirements of Industry 5.0.

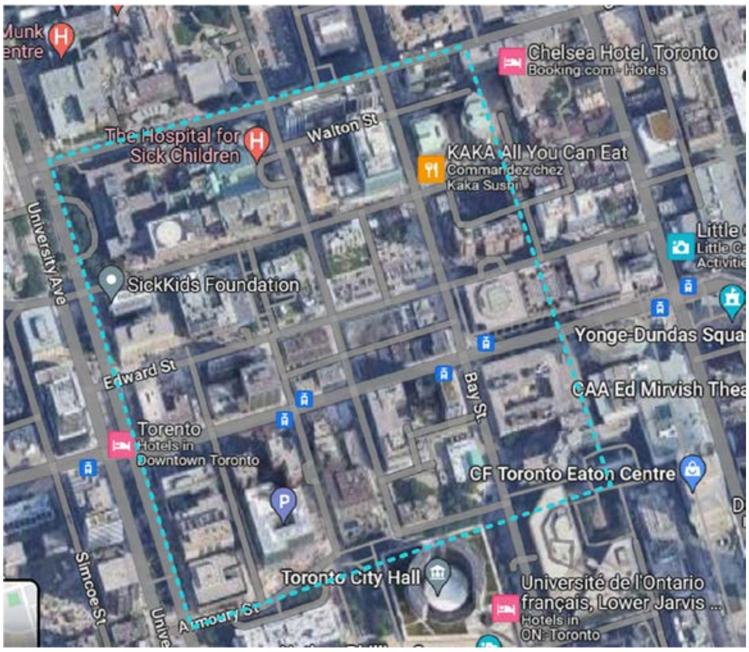

Fig. 3. Urban environmental map.

Before conducting urban patrol tasks with drones, it is necessary to first plan a feasible flight path for the drones [27]. The purpose of the unmanned aerial vehicle (UAV) based patrol system designed in this study is to complete patrol tasks in smart cities with minimal energy consumption while protecting public privacy, providing technical support for emergency response and post disaster recovery in smart cities. **Fig. 3** shows a real urban environment map. In the urban environment, there are a large number of buildings distributed on both sides of the street. Therefore, drones need to avoid obstacles during patrol tasks.

At the same time, the purpose of drones conducting patrols in urban environments is to collect as much information as possible by hand, in order to avoid the occurrence of danger. For example, during the patrol process of drones, it is necessary to capture images of the external obstacles in order to avoid the falling of high-rise building objects and posing a threat to pedestrians on the ground. Drones should avoid generating noise during patrols, which can have an impact on human beings in the city, aiming to embody the people-oriented goal in Industry 5.0. In addition, during the patrol process, drones should minimize their flight path as much as possible, in order to consume less energy and further achieve the goal of reducing carbon emissions. For these three purposes, this article establishes a multi-objective mathematical model as follows.

4.1 Mathematical Model of UAV Patrol Task

Before establishing the model, some symbols used in this study were explained, as shown in **Table 1**.

Table 1. Symbol description

Symbol	Description
A	The set of buildings, $A=\{1,2,\cdots,a_{\max}\}$
$\mathrm{M}(a)$	The collection of grids that make up the outer surface of building a, $\mathrm{M}(a)=\{a_1,a_2,\cdots,a_{\max}\}$
B	The set of flight path points for the drone, $B=\{1,2,\cdots,b_{\max}\}$
$C(a_m)$	The coordinates of the center point of the grid, $C(a_m)=(x(a_m),y(a_m),z(a_m))$, $\forall a_m \in \mathrm{M}(a)$
$C(b)$	The coordinates of the drone's trajectory point, $C(b)=(x_b,y_b,z_b)$, $\forall b \in B$
$\beta_{\max}$	The maximum yaw angle of the drone
$\alpha_{\max}$	The maximum tilt angle of the drone
$v_{\max}$	The maximum flight speed of the drone
T_b	Flight time of the drone in track segment $b-1 \to b$
l_b	Flight distance of the drone in track segment $b-1 \to b$
$T_{\max}$	Effective range of the drone
$\lambda_{\max}$	Maximum shooting angle of the camera
$L_{\max}$	Maximum shooting distance of the camera

4.1.1 Area of Patrols

During the drone patrol process, the drone collects information through its equipped camera. During drone flight, it is possible to determine whether the image information of streets and buildings has been collected based on the maximum shooting angle and optimal shooting distance of the camera. The CPSS based patrol system aims to collect information on buildings, roads, and other contents of the city to the maximum extent possible. The objective function is as follows:

$$\max f_1 = \sum_{a_m \in M(a)} \sum_{b \in B} S(a_m) \times \varphi_{a_m,b} \tag{1}$$

where, $\varphi_{a_k,b}$ is a 0-1 variable. When the drone is at track point b, $\forall a_m \in \mathrm{M}(a)$, if grid a_m can be captured, $\varphi_{a_k,b}=1$, otherwise $\varphi_{a_k,b}=0$.

$$l(a_m) = \sqrt{\left[z(a_m) - z_b\right]^2} \tag{2}$$

$$S(a_m) = \pi \times (z(a_m) \times \tan(\lambda_{\max}/2))^2 \tag{3}$$

$$\cos(a_m) = \frac{\dot{e}(a_m,b) \cdot \dot{n}}{\left|\dot{e}(a_m,b)\right| \cdot \left|\dot{n}\right|} \tag{4}$$

$$\varphi_{a_k,b} = \begin{cases} 1, & l(a_m) \le L_{\max} \ \& \cos(\lambda_{\max}) \le \cos(a_m) \\ 0, & others \end{cases} \tag{5}$$

Equation (2) calculates the distance $l(a_m)$ from the UAV flight position to the surface of the patrol area. Equation (3) is the calculation method for the swept area of patrols $S(a_m)$. When the relative positions of the drone's trajectory point b and the grid point $\forall a_m \in \mathrm{M}(a)$ meet both Equations (2) and (4), the drone can capture the grid. The vector $\dot{e}(a_m,b) = (x(a_m) - x_b, y(a_m) - y_b)$ is shown in (5), vector $\dot{e} = (0,0,-1)$ is a vector perpendicular to the ground.

4.1.2 Carbon Emissions

The carbon emissions of drones during the patrol process are also one of the goals of the patrol subsystem. Because Industry 5.0 has high requirements for sustainability. Therefore, the patrol subsystem also aims to reduce carbon emissions of the drone, making smart cities more sustainable. During the flight of drones, carbon emissions and energy consumption are directly related to the flight distance of UAV [16]. Therefore, the model for minimizing carbon emissions during the patrol process of UAV is shown in (6).

$$\min f_2 = \sum_{b \in B} Ce_b \tag{6}$$

$$l_b = \sqrt{\left(x_{b-1} - x_b\right)^2 + \left(y_{b-1} - y_b\right)^2 + \left(z_{b-1} - z_b\right)^2} \tag{7}$$

$$Ce_b = n_{co} \times l_b \tag{8}$$

Equation (7) shows the calculation method for the flight distance of the drone in trajectory segment $b-1 \to b$. Equation (8) provides the relationship between carbon emissions and flight distance, where n_{co} is the carbon emission coefficient.

4.1.3 Noise Impact

Furthermore, an important component of CPSS is the social system, which is also the focus of this study. As stated in the second section of the study, the adverse effects of drones operating in urban environments on society need to be addressed in order to better align with the people-oriented goals of the Industrial 5.0 paradigm. The adverse effects of drones operating in urban environments mainly include noise. According to the work in references [37]-[38], it can be inferred that when the flight altitude of drones is high enough, the impact of noise generated by drones on humans can be ignored. Therefore, in order to reduce the impact of noise on human society, a mathematical model is established as follows.

$$\min f_3 = \sum_{b\in B} \theta_b \times (Z_{noise} - z_b) - \sum_{b\in B} \theta_b \tag{9}$$

$$\theta_b = \begin{cases} 1, & Z_{noise} \geq z_b \\ 0, & Z_{noise} < z_b \end{cases} \tag{10}$$

where, θ_b is a 0-1 variable. When the drone flies at track point *b*, the flight altitude causes noise pollution to the city, $\theta_b = 1$, otherwise $\theta_b = 0$; Z_{noise} is the standard altitude at which the drone generates noise; when the flying altitude of the drone is higher than Z_{noise}, no noise is generated, otherwise, noise is generated. Therefore, the objective function consists of two parts. The first part is that during the flight of the drone, there should be as many track points as possible without generating noise at the flight altitude; The second part is that when the flying altitude of drones has an impact on cities, the flying altitude needs to be as high as possible to reduce the impact of drone noise on humans in cities.

4.1.4 Objective Function and Constraint Conditions

According to the method of dealing with multi-objective functions in reference [16], this paper establishes a multi-objective mathematical model as shown in (11). Furthermore, due to the fact that the flight trajectory of unmanned aerial vehicles during flight needs to meet the constraints of maximum tilt angle, maximum yaw angle, battery capacity, and other unmanned aerial vehicle trajectory constraints. In the process of drone trajectory planning, there are mainly two planning methods. The first method is to keep the distance step constant and constrain the flight time of the drone; The second method is to maintain a constant time step, which constrains the distance of the drone per unit time [32]-[34]. In this study, a constant time step T_b was chosen. Therefore, in order to establish a complete mathematical model of unmanned aerial vehicles, according to references [35]-[36], the constraint conditions are defined as follows.

$$\begin{aligned} \min f &= \frac{1}{f_1} \times f_2 \times f_3 \\ &= \frac{1}{\sum_{a_m \in M(a)} \sum_{b\in B} \varphi_{a_m,b}} \times \sum_{b\in B} l_b \times \left[\sum_{b\in B} \theta_b \times (Z_{noise} - z_b) - \sum_{b\in B} \theta_b \right] \end{aligned} \tag{11}$$

$$\frac{\dot{m}_b^{\mathrm{T}} \cdot \dot{m}_{b+1}}{|\dot{m}_b| \cdot |\dot{m}_{b+1}|} \geq \cos(\beta_{\max}) \tag{12}$$

$$\frac{|z_b - z_{b-1}|}{|\dot{m}_b|} \leq \tan(\alpha_{\max}) \tag{13}$$

$$\frac{l_b}{T_b} \leq v_{\max} \tag{14}$$

$$\sum_{b\in B} T_b \leq T_{\max} \tag{15}$$

Formula (12) is the maximum yaw angle constraint for the drone, where $\dot{m}_b = (x_b - x_{b-1}, y_b - y_{b-1})$. Formula (13) is the maximum tilt angle constraint for the drone. Formula (14) is the maximum flight speed constraint for the drone. Formula (15) is the battery capacity constraint for the drone.

4.2 Heuristic Algorithm Design

It can be concluded from a large amount of related work on drone trajectory planning, such as [16], [30]-[36], that heuristic algorithms are commonly used in current drone trajectory planning methods. Therefore, this study also selects heuristic algorithms for trajectory planning, aiming to enable drones to successfully complete patrol tasks and apply them to smart cities. The ACO and DE algorithms are widely used in large-scale optimization problems due to their advantages such as fewer parameters and fast solving speed [32]-[33].

The ACO algorithm used to solve optimization problems draws inspiration from the foraging process of ant colonies, where each individual selects the corresponding path node based on pheromones. During an iteration, when all individuals search from the starting point to the endpoint, the pheromones on all path nodes are updated and a new search begins [32]. In the process of solving optimization problems, the DE algorithm searches through cross mutation and individual selection [34]. In order to further improve the performance of the algorithm, this paper integrates the search strategy of the DE algorithm with the search strategy of the ACO algorithm, and designs a novel metaheuristic algorithm, the DE-ACO algorithm. Algorithm 1 shows the pseudocode of the DE-ACO algorithm.

Algorithm 1: DE-ACO algorithm

Input: Population size Q, maximum number of iterations W_{MAX}, pheromone importance factor κ, pheromone volatility factor ψ, mutation operator μ, crossover operator θ, individual dimensions $B_{\max}$, initial trajectory set generated based on RRT algorithm $\{Path_{RRT}\}$.

Output: The optimal set of trajectory points.

$W \leftarrow 1$
$\{Path_q\} \leftarrow \{Path_{RRT}\}$
while $W \le W_{MAX}$ do
    for i=1to Q do
        for b=1to $B_{\max}$ do
            if $P(W) \ge 0.5$ then
                /*The pheromone-based differential evolution strategy*/
                if $rand(W) \le 0.5$ then
                    $u_{q,W+1} \leftarrow v_{q,W+1}$
                else
                    $u_{q,W+1} \leftarrow b_{q1,W+1}$
                end
            else
                /*The mutation-crossover operations*/
                $t_{q,W+1} \leftarrow b_{q1,W} + e^{j} \times \cos(2\pi j)$
            end
        end
    end
    $W \leftarrow W+1$
end
return the best vector

4.2.1 DE-ACO Algorithm

In order to further improve the search ability of the ACO algorithm, a differential evolution strategy based on pheromones has been designed. The specific steps of the DE-ACO algorithm are as follows.

Step 1: Initialize the relevant parameters of the algorithm. This includes parameters such as population size Q , maximum number of iterations W_{MAX} , pheromone importance factor κ , pheromone volatility factor ψ , mutation operator μ , crossover operator θ , etc.

Step 2: Randomly generate an initial population and construct a solution space. Use the RRT algorithm to generate an initialization trajectory equal to the population size Q based on the starting and ending points of the drone.

Step 3: Calculate the fitness function value F of each individual in the population, as shown in (16).

$$F = \frac{1}{\sum_{a_m \in M(a)} \sum_{b \in B} \varphi_{a_m,b}} \times \sum_{b \in B} l_b \times \left[\sum_{b \in B} \theta_b \times \left(Z_{noise} - z_b \right) - \sum_{b \in B} \theta_b \right] \tag{16}$$

Step 4: Adopting the pheromone-based differential evolution strategy to perform mutation crossover operations on some individuals of the entire population. Specifically, first calculate the pheromone concentration $PH_{con}(W)$ of the current individual at the current iteration number based on (18) and (19).

$$\Delta PH_{con} = \frac{F(W)_q - F_{\min}}{F_{\max} - F_{\min}} \tag{17}$$

$$PH_{con}(W) = (1-\psi) \times PH_{con}(W-1) + \Delta PH_{con} \tag{18}$$

$$P(W) = \frac{PH_{con}(W)^{\kappa}}{\sum_{W} PH_{con}(W)^{\kappa}} \tag{19}$$

where, $F_{\max}$ and $F_{\min}$ are the contemporary optimal objective function values and the contemporary worst objective function values generated in the iteration number W . $F(W)_q$ is the fitness function value of individual q when the number of iterations is W . $P(W)$ is the transfer probability based on pheromones.

When $P(W) > 0.5$, individuals perform mutation-crossover operations according to (20) and (21).

$$v_{q,W+1} = b_{q1,W} + \mu \times \left(b_{q2,W} - b_{q3,W} \right) \tag{20}$$

where, $v_{q,W+1}$ is the mutated vector; $b_{q1,w}$ is the b -*th* vector of the individual $q1$ in the W -*th* iteration process, and $q1 \neq q2 \neq q3$.

$$u_{q,W+1} = \begin{cases} v_{q,W+1}, & rand(W) \leq 0.5 \\ b_{q1,W+1}, & rand(W) > 0.5 \end{cases} \tag{21}$$

where, $rand(W)$ is a random number in the interval [0,1]; $u_{q,W+1}$ represents the individual after crossing.

Step 5: Perform information correction operations based on the spiral rule on another part of the population.

When $P(W) \le 0.5$, the individual performs information correction operations based on the spiral rule according to (22).

$$t_{q,W+1} = b_{q1,W} + e^{j} \times \cos(2\pi j) \tag{22}$$

where, j is the random number between intervals [-1,1], and $t_{q,W+1}$ is the vector after the mutation.

Step 6: Calculate the fitness function value of each individual, with iteration number $W = W + 1$, to determine whether the termination condition has been met. If so, output the result. If not, return to ***Step 4***.

4.2.2 Computational Time Complexity Analysis

In traditional DE algorithms, the search process consists of three single loops, and the fitness function value of each individual in the population is calculated twice. According to work [35],[39], the time complexity $O(DE)$ of the DE algorithm is defined as follows:

$$O(DE) = O\left(T\left(O(T_1 + T_2 + T_3)\right)\right) = O\left(Q * B_{\max} + W_{\max} * Q * (1 + \log N + B_{\max})\right) \tag{23}$$

where $O(Q * B_{\max})$ is the time complexity of initialization, $O(Q)$ is the time complexity of calculating the fitness function, $O(Q * B_{\max})$ is the time complexity of the search process, and $O(Q * \log N)$ is the time complexity of sorting the fitness function.

Algorithm 1 and section 4.2.1 show all the steps of the DE-ACO algorithm, and the search process of DE-ACO consists of four single loops. The fitness function value of each individual in the population was also calculated twice. Although the loops in the search process of the DE-ACO algorithm have increased, the time complexity of the search process is also $O(Q * B_{\max})$. Therefore, the time complexity $O(DE - ACO)$ of the DE-ACO algorithm is defined as follows:

$$O(DE - ACO) = O\left(T\left(O(T_1 + T_2 + T_3)\right)\right) = O\left(Q * B_{\max} + W_{\max} * Q * (1 + \log N + B_{\max})\right) \tag{24}$$

4.3 Results Display

In this section, based on the mathematical model and algorithm designed in this study, a simulation example for a real urban scenario is presented. All simulations are run in the Matlab environment. Based on the urban environment shown in **Fig. 3**, a three-dimensional digital environment model was established in the cyber system, and **Fig. 4** shows a three-dimensional digital environment map. In order to ensure the fairness of simulation experiments, this study selected existing algorithms for UAV trajectory planning and DE-ACO algorithm for comparison. Specifically, this study selects the IACO algorithm from work [32]-[33], the DE algorithm from work [34]-[35], and the IGSO algorithm from work [24], [36] for comparison. To verify the robustness of the algorithm designed in this study, all algorithms were run 30 times.

Fig. 5, **Fig. 6**, and **Fig. 7** respectively show the optimal fitness function curves, worst fitness function curves, and average fitness function curves of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm during 30 runs. Furthermore, **Table 2** shows the optimal fitness function values, worst fitness function values, and average fitness function values of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm during 30 runs.

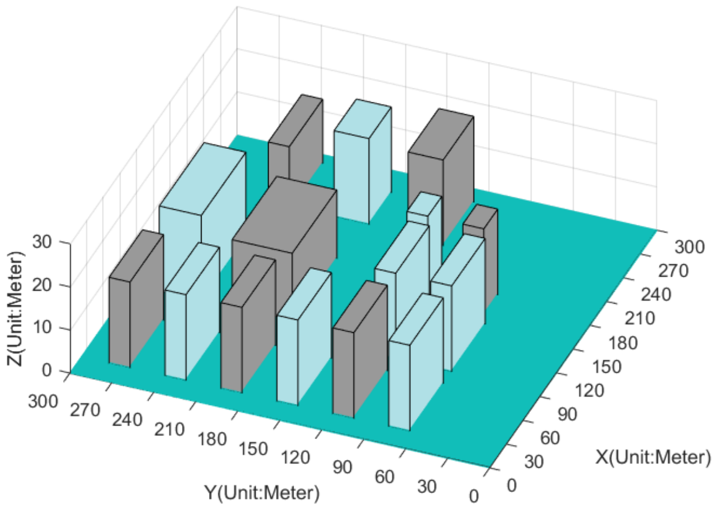

Fig. 4. Digital environment map.

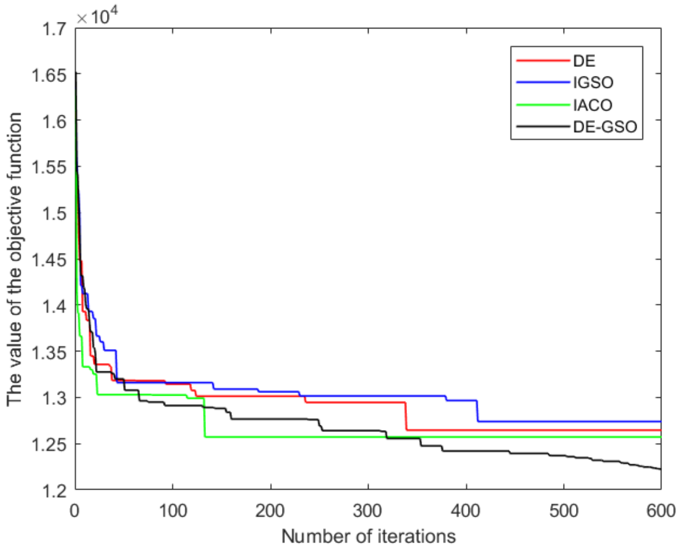

Fig. 5. Optimal fitness function curve.

Fig. 5 shows the optimal fitness function values of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm during 30 runs. Among them, the optimal function value of DE algorithm is the smallest, with a value of 12230.39. The optimal fitness function values of DE algorithm, IACO algorithm, and IGSO algorithm are 12878.73, 12666.69, and 12833.45. The optimal fitness function value of the DE-ACO algorithm is 5.31% lower than that of the DE algorithm; 3.57% lower than the IACO algorithm; 4.93% lower than the IGSO algorithm.

Fig. 6 shows the optimal fitness function values of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm during 30 runs. Among them, the worst fitness function value of DE algorithm is the smallest, with a value of 12247.23. The worst fitness function values of DE algorithm, IACO algorithm, and IGSO algorithm are 12947.51, 12925.06 and 12997.65, respectively. The worst fitness function value of the DE-ACO algorithm is 5.72% lower than that of the DE algorithm; 5.53% lower than the IACO algorithm; 6.13% lower than the IGSO algorithm.

Fig. 7 shows the average fitness function values of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm over 30 runs. Among them, the average fitness function value of DE algorithm is the smallest, with a value of 12233.08. The average fitness function values of DE algorithm, IACO algorithm, and IGSO algorithm are 12820.42, 12814.58, and 12878.16. The average fitness function value of the DE-ACO algorithm is 4.80% lower than that of the DE algorithm; 4.75% lower than the IACO algorithm; 5.27% lower than the IGSO algorithm.

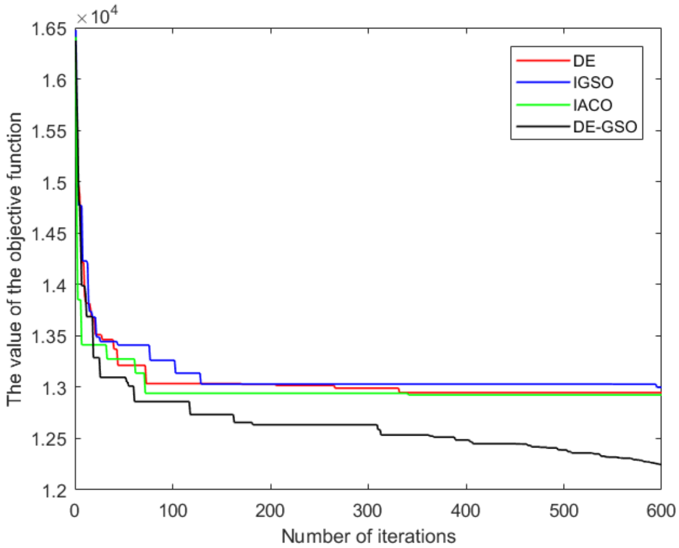

Fig. 6. The worst fitness function curve.

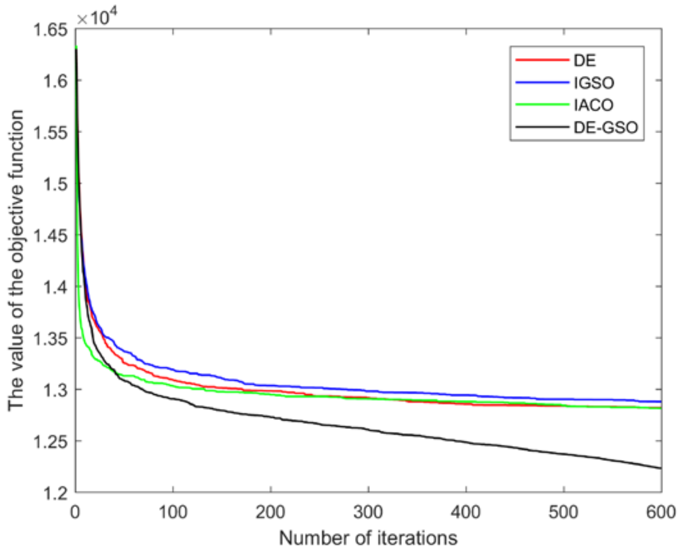

Fig. 7. The average fitness function curve.

Table 2. The fitness function values for four algorithms running 30 times.

Objective Function Value	Algorithms			
	DE	IGSO	IACO	DE-ACO
Optimal	12878.73	12833.45	12666.69	12230.39
Worst	12947.51	12997.65	12925.06	12247.23
Average	12820.42	12878.16	12814.58	12233.08
Std	72.1123	70.8871	84.1500	5.5354

Table 3 shows the average patrol area, carbon emissions, and noise impact of the DE algorithm, IACO algorithm, IGSO algorithm, and DE-ACO algorithm during 30 runs. **Fig. 8** shows the trajectory map of a randomly selected trajectory planning result of the DE-PSO algorithm during 30 runs. According to **Table 3**, it can be concluded that the DE-ACO algorithm has the maximum average patrol area of 0.062774 km^2 after running the four algorithms for 30 times; The average carbon emissions of the DE-ACO algorithm are the smallest, at 1.392071; The noise impact of the DE-ACO algorithm is the smallest, at 551.6381.

Table 3. The average values of patrol area, carbon emissions, and noise impact for 30 runs of four algorithms.

Objective Function Value	Algorithms			
	DE	IGSO	IACO	DE-ACO
Area of Patrols (km^2)	0.05885	0.051329	0.056735	0.062774
Carbon Emission	1.568135	1.623184	1.576327	1.392071
Noise Impact	578.4934	590.2356	577.2569	551.6381

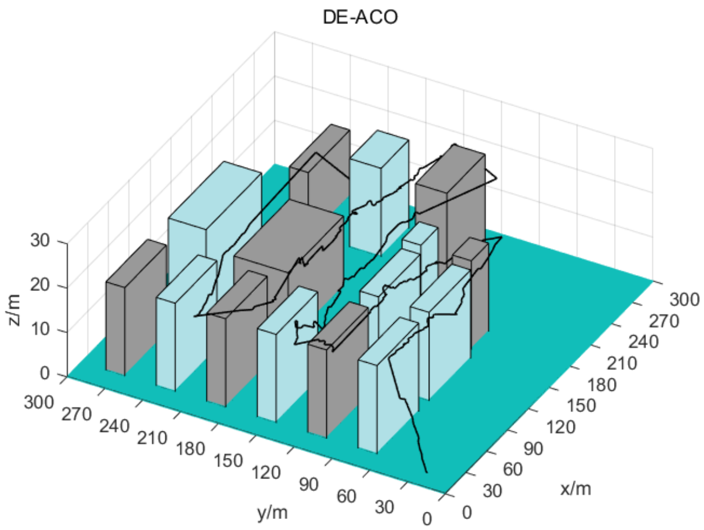

Fig. 8. The trajectory map of the DE-ACO algorithm.

5. Conclusion

Based on the new requirements of the Industrial 5.0 paradigm for smart cities, this article focuses on the construction of low-carbon smart cities that are people-oriented from the perspective of SGDs. In order to further highlight the goal of putting people first in future cities, a smart city framework based on physical-social space and cyber-space has been proposed according to parallel system theory, and a new smart city paradigm has been established, parallel cities. In order to further demonstrate the goal of making parallel cities more sustainable and people-oriented, this article establishes a smart patrol subsystem for parallel cities, and proves the effectiveness of the algorithms and models used in the smart patrol subsystem through a simulation. In further research, a series of parallel systems such as smart transportation systems, smart healthcare systems, and smart education systems in parallel cities will be established.

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