International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 3 ǁ March 2023 ǁ PP. 557-566

Fundamental Elements of Drone Management Systems in Air Traffic Planning

Hong-Tien Nguyen [1], Xuan-Long Trinh [2], Van-Tai Nguyen [1], Quang-Khai Phung [1], Vuong-Thao Tran [3], Manh-Hung Duong [2], and Dinh-Dung Nguyen [2,*]
[1] Faculty of Aeronautical Engineering, Air Defence – Air Force Academy, Hanoi, Vietnam
[2]Faculty of Aerospace, Le Quy Don Technical University, Hanoi, Vietnam
[3] Technical Department of Air Defence – Air Force, Air Defence – Air Force, Hanoi, Vietnam
** Corresponding Author: Dinh-Dung Nguyen*

Abstract
Drones or Unmanned Aerial Systems (UAV- Unmanned Aerial Vehicles or U.A.S.- Unmanned Aerial Systems) are vehicles that can fly without a pilot or passengers. Drones can be controlled remotely through radio waves or independently (with a previously determined route). The amount of documented accidents involving the hazardous use of drones has risen significantly due to the increased usage of drones. A variety of regulations and management procedures will be implemented to perform and increase the use of drones in air traffic management (A.T.M.), especially in smart city planning. This paper proposes management rules or regulations for drones in smart city transportation management and some approaches related to drone management and control. To present controlling techniques through the parameters in mathematical modeling for drones, we need a control rule, data gathering from the surroundings (Usage of G.I.S.), and a dynamic model of drones, and to present controlling and managing it with the help of a drone-following model based on a dynamic model of drones.
Keywords: *UAV, Drones, Smart Cities, Urban Air Traffic Management.*

Date of Submission: 14-03-2023 Date of acceptance: 29-03-2023

I. INTRODUCTION

Recently, the world's leading scientists and high-tech pioneers have announced their intention to develop and manufacture a wide range of affordable small controlled from a distance or self-managed flying vehicles known as drones (unmanned aerial vehicles/systems—UAV, U.A.S., including even small pilot-less air vehicles, or air taxis). A variety of UAVs (unmanned aerial vehicles) have been widely exercised in both civil and military services, resulting in excellent utilization efficiency [1], [2], [3]. Moreover, drones are expected to serve as a vital part of the smart city with several use cases, including transportation [4], medical [5], and agricultural industries [6], in addition to military applications.

In addition to this, a severe obstacle prevents the instantaneous integration of drones into present operations, particularly in smart city designs, where mobility is a crucial consideration [7], [8]. The current air traffic management systems (A.T.M.) are not able to manage the indicated number of UAVs that operate at lower altitudes in the urban region between tall and large structures and complex environmental circumstances due to (i) system capacity and limitations, (ii) necessary workforce, (iii) predicted income and expenses, and (iv) required duration of system development [9], [10].

Order to enable drones to operate on a routine schedule is an essential aspect of the air transportation strategy in urban areas. It's also critical to design methodologies that solve these technical problems with a specific legislative framework and establish management systems for securely operating operations, both in the air and on the ground. The identifying method of the mathematical model can be used to synthesize higher-quality control systems in this case. Furthermore, drone-following models defining the one-by-one following the process of drones in interflow traffic are required for the examination of drones' security and safety in air traffic as well as the creation of smart transportation systems.

Finding a UAV's mathematical model is one of the most important aspects of drone design. It confirms that the mathematical model of the control object recognition method has seen significant development in recent years, which is critical for the development of a high-quality automatic control system for drones. This method allows us to efficiently determine the mathematical model object, whose control is based on data from input and output signals to the controller object.

When the number of drones grows, serious incidents might occur in the airspace, even in relatively harmless scenarios. Hereby necessitates the development of a drone management system, which is a component of the overall unmanned traffic management system (UTM) that ensures safe, environmentally friendly, efficient, and long-term transportation in urban/city regions. These sub-systems work simple; however, they have quick interconnections with air traffic management systems, allowing them to perform tasks such as sharing airspace, detecting and resolving conflict/obstacles, and determining optimal trajectory control. New modes of transportation, such as urban air transportation (drones, air taxis), must now be incorporated into the overall transportation management system and coordinated with other autonomous vehicles.

G.I.S. is also one of the essential parts of the drone management system. The G.I.S. operators or authorities have to notify the drone air traffic management headquarters of scheduled flights and the estimated locations before the flights. The automated center creates the route for a specific flight in a 3D virtual channel optimized by using a G.I.S. map and creates a slot depending on other people's trajectories and surrounding information. The procedure should be restarted if the drone passes the available slot. The drone's flight is completely automated, yet it constantly assesses its location potential for conflict and adjusts its speed to the actual flight circumstances. Drones are tracked through G.P.S. and G.I.S. mapping, using active intelligence surveillance and reference points in the buildings.

Moreover, an essential part of the drone management system is the usage of drone-following models that describe the one-by-one tracking of drones through traffic flows. Drone-following models work by calculating the drone's acceleration based on the differences in velocities and distances between the drone in consideration and the drone in front of it (S.D. models). Furthermore, Markov drone-following is an enhanced technique based on a stochastic diffusion process of speed decisions estimation. When SD models are no longer sufficient, this model is applied. The Markov drone-following model can assess conditions that are only manageable by advanced controllers.

The focus of this research is to propose methods for identifying parameters in a mathematical model of a drone as a control object, as well as to merge drone management and control systems. To provide a drone management system and their transportation, particularly in smart cities, operational concepts for drone operations in urban areas must be presented, including airspace design, recommended airway construction, and critical safety standards. For route planning and information collection of drones usage of G.I.S.s. Drone-following models are also required to analyze drone traffic safety and develop an intelligent transportation system. The two main drone-following models discussed in this study are the S.D. models and the Markov drone-following model.

II. MATERIALS AND METHODS

2.1. Parameters of mathematical model of drones

Theoretically, identifying an unknown drone parameter may be accomplished in two ways: one, by directly calculating the drone's geometry, and the other, by analyzing the flight data. The first technique demands complex mathematical and physical computations with a high processing workload; however, the second technique requires a simple algorithm that produces more precise results than the first technique.

The least-squares error method is an identification method utilized in this research [11], [12], [13]. It is a technique that enables determining the mathematical model of an object with high efficiency, with those of the control based on data from input and output signals to the controlling object. Based on a recognition algorithm that is being used to determine a drone. As follows, precisely: The mathematical model simulates, then data is gathered in order to carry out the identification. The identification results are then assessed by comparing the pattern model to various input signals.

Additionally, drones, particularly quadrotors, were developed to be hand-operated, thus distinguishing input and output data using onboard sensors to establish the mathematical model would build a somewhat realistic, more accurate mathematical model using the modeling method. Furthermore, the least-squares error method's approach is simple to comprehend and implement, and it allows for the computation of variables, resulting in a mathematical model of a controlled element that is generally accurate.

Before applying the mathematical model identification, we must start with building a basic control system, so this can allow the collection of the input and output signals of the system. Then, we can fully carry out the mathematical model identification. The identifying process should be carried out several times in various flight conditions, then perform calibration parameters. The aim of mathematical model identification is to ensure with the impact of noise, different signal types change input signals and the output signals of the recognition models should continuously be aware of the output signals of the model. As a result, the mathematical model can detect and characterize the drone's movements along with its channels with high precision.

2.2. Drone management systems

The growing number of drones offers significant issues in aviation, particularly in air traffic control. As a result, different operational characteristics must be developed to protect daily flights in terms of safety and implementation by operators. The suggestion of UAV traffic management systems (UTM) is to assist in the successful completion of the flight and effective control of overall air traffic. A system such as this might be controlled to improve the separation between UAVs and aircraft that have been used on regular flights, as well as traffic flow order in extremely low-level airspace regions. Because of the data it receives, this system operates independently of air traffic management systems (A.T.M.s). Moreover, because drones fly in 3D space, they are affected by strong gusts of wind flow. Isolation from structures and air turbulence is a problem that is more complicated than it is for road vehicles.

Drone management is divided into six categories, each of which is based on a systematic concept:

- Non-detected objects: those that do not occur on the surveillance screen;
- detected objects: those that do occur on the surveillance screen, although this is uncertain if they are passive, non-cooperating, or demonstrate non-relevant targets, like as birds;
- Semi-active or simple cooperative objects: which give the operation center with at minimum partial relevant data;
- Active or cooperative objects or service providers: those submit data on the objects located in the urban setting; accessible data should also include data on the vehicle type, its identification number, load, current position, intention, and the final route;
- Connecting vehicles that cooperate and coordinate their motions passively or actively, e.g., flying in order, or utilizing conflict prediction, management, and solution, based on relevant data being presented;
- Contract-based drones with certain preferences, that are contract-based and therefore must pay for the service offered.

Management and control of air traffic and the flights for drones or groups of drones are in high demand [14], [15], [16]. Drones could be programmed to follow predetermined paths or corridors. Sensor fusion, fixed trajectory flowing models, centralized dynamic sectorization, active management, real-time G.I.S. support, preset flight configurations such as flight drone following models, coordinated maneuvers, active disaster detection and resolution, and formation flights should all be used to assist and guide the drone operation. Drones flying in city areas are likely to operate at lower heights and between structures in the sky, going to create a lot of turbulence, which is generated in effect separation from constructions by wind (flow). Consequently, particular approaches of automation, such as vehicle following models, are possibly drastically dissimilar and unlikely in vehicle and drone traffic. Thereby, flying across a tight gap is one of the most difficult autonomous drone control challenges. It necessitates the drone passing through the center with its level aligned with the gap's positioning, reducing the possibility of a crash. The one-by-one following drone method in "narrow corridors" between the residences without the need for a conventional planning and control piping system is one solution for this issue.

Moreover, one of the fundamental properties of the drone management system is sensor fusion tools which are unmanned systems based on sensor arrays that collect information of themselves and sensors that detect the surroundings. Radar systems and vision cameras are examples of sensors that perceive their environment and detect objects in their range of perception. In addition, these sensors have Lidars, a remote sensing method that provides information about the obstacles around the surrounding of a drone. The sensor system does some signal processing to reduce nuisance alarm, including identification, segmentation, classification, labeling, and, in some cases, simple tracking.

Various research looks into flight planning involving environmental uncertainties, specific aggressive maneuvers, and flights with low altitude. Backstepping route-following control, barometric altimeter monitoring fault diagnosis technique utilizing neural feedforward systems, P.I.D. Controller with multi-loop design, Infrared camera, and beacon systems, path planning, and route following may be improved by feedback linearization control-oriented algorithms, non-linear guiding regulations, or carrot-chasing geometric algorithms. Drones ought to maintain predetermined paths, routes, or corridors inside the aviation data network. Drones' exact location and mobility can be measured in the surroundings using sensors installed in metropolitan areas.

Another significant factor of the drone management system is the obstacle avoidance method. Drone flights require a collision-avoidance system to maintain airspace security, particularly for autonomous drones flying in busy airspace used with other aircraft. The obstacle model is one of the essential components of drone simulation tools. Consider that every other obstacle is represented by a cylinder with a radius r_{Bl} and a center C_{Bl} (Figure 1). The surfaces of cylinders could also be used to provide obstacle avoidance constraints. At the flying altitude, the safe distance $d_{s,l}$ from the same obstacle l is evaluated precisely from the cylinder center toward its surface.

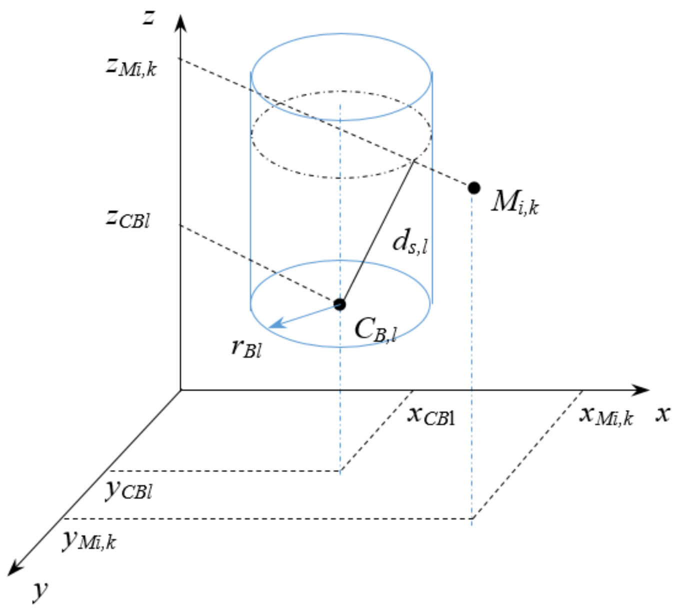


Figure 1: Representation of the obstacle avoidance method

The landing approach is also one of the most crucial components of the flight since it ensures that the UAV lands safely at the designated position. The phases of a standard landing process are as follows: flying against the wind, descending, and slowing down. Several elements, however, may affect this process, including wind turbulence, general aerodynamic force, engine traction force, and propeller reaction moment. The landing regions are determined and calculated using analytical methods and the solution of the aircraft's equations of motion. The intended landing orbit is predicted based on the landing zones, enabling the UAV to land precisely at the intended location.

2.3. G.I.S. applications in drones

Since the 18th century industrial revolution, urban planning, and urbanization problems have occurred due to the rapid increase in the global population and the concentration of the inhabitants for some locations [17]. For policymakers, this unnatural rapid urbanization has caused substantial environmental and social problems [18]. Modeling and simulation technologies are critically efficient instruments for delving into the dynamics of urban development and facilitating growth management planning. As a result, monitoring and modeling city expansion is a critical component for avoiding future difficulties [19], [20].

Every city is a complex system. Geographical information systems combine all spatial and non-spatial information in a single system. While providing consistency in the analysis of geographical data, it establishes various connections and relationships between events depending on geographical proximity and ensures that all stakeholders access this data and analysis under a single platform. G.I.S. can integrate spatial data with other data sources. Web scenes provide a realistic perception by showing geographic data and events in three dimensions. All geographic layers can be mapped with three-dimensional symbology. Performs the generation and presentation of G.I.S. maps on the computer.

Urban life requires a high level of understanding and solutions to the challenges faced by the society in that city. It is one of the high-tech application areas where large amounts of data are needed. Big data means that complex urban systems facing some challenges; They are large amounts of data with a variety of characteristics that have the ability to make new theories and approaches for investigating interconnections between the social, biophysical, and other industrial fields [21], [22], [23].

In G.I.S., area data are usually represented by mosaicing, and object data by topological vector data. Mosaic, which is formed by the coming together of surrounding cells, is of three types: square cells, hexagonal cells, and triangular cells. However, all cells have the same shape and size within themselves. Each cell is assigned a value and these values are related to all other cell values. The tessellation process takes place in many G.I.S. software with different names such as raster or raster map. The size of a single raster cell is called raster resolution. The structure formed by these cells is called a grid.

Drones can follow fixed trajectories or predefined corridors. For this, real-time G.I.S. support is one of the requirements. Thus, active conflict/obstacle detection and problem resolution can be achieved. G.I.S. support can be provided by 3D modeling.

The digital terrain model represents the geographical structure or the real terrain in the area. In other words, it enables the structure of the land to be expressed digitally in all aspects, such as elevation, slope, aspect direction, drainage, etc. In this way, sustainable G.I.S. mapping support can be obtained for integration into transportation systems in smart cities.

High-resolution maps are the cornerstone of evaluating urban footprints by integrating them into global settlement models. In the last ten years, rapid progress has been made in the providence of this spatial information. The following covers a compilation of specific datasets, which has great importance, with GIS-based information in the field of urbanization:

- Global Map: A global map is a collection of mapping software that covers the entire globe and precisely represents the condition of the terrain and the surroundings on a global scale. It was established with the help of National Geospatial Information Authorities (NGIAs) from all around the world. With a minimum surface resolution of 1 km for raster data and a ratio of 1: 1,000,000 for vector data, the Global Map offers eight main map concepts.
- These concepts are: (i) Transportation, (ii) Boundary, (iii) Drainage, (iv) Population Centers, (v) Height, (vi) Flora, (vii) Land Cover, (viii) Land use
- World's Grid Population (G.P.W.): The population density of past, current, and projected raw population statistics are included in this collection from NASA's socioeconomic data and processing center. G.P.W.'s purpose is to provide a geographically disaggregated population layer that may be used with datasets from sociological, economical, and Geoscience departments, as well as satellite data. These data are accessible to research, spatial decision-making, and communication on a worldwide scale.
- World Bank Geodata: A huge spectrum of World Bank databases, including economical and educational datasets, have been transformed to K.M.L. format in this data.
- Global Management Fields: These are the database sections of low-level information belonging to administrative fields such as countries and provinces. Version 3.6 was released in 2018. Version 4 will be released in December 2021. Researchers can collect geographical information from every nation, which contains 386,735 administrative locations.
- Armed Conflict Location and Incident Dataset: Updated constantly, starting from 1997 to the present time, this dataset contains all documented conflict incidences information of 50 developing countries.
- Global Rural-Urban Mapping Project (GRUMP): It is a data set containing information about rural and urban population balances, taken from NASA's socioeconomic data and application center.
- Open Street Map (O.S.M.): Worldwide landmarks, infrastructures, roads, streets, ship routes, etc. It is crowdsourced data that contains much important information.
- Geohive8: Ordnance Survey Ireland has made Geohive8 available for easily accessible to 'public spatial data,' which covers demographic and county data. It's not in G.I.S. data format, but it's simple to convert from CSV format [24].

2.4. Drone following models

The drone following models stand as a significant part of the drone management system. They are models that calculate the drone's acceleration based on the velocities and distances between the particular drone and with the drone that is leading. Drone-following models are being designed for the purpose of building speed profiles close to the actual situation, the capacity to produce actual traffic flows, steady awareness of traffic conditions, modeling of traffic situations noticed by varying configurations of drones and control system variables, and the ability to implement them in traffic control systems (Figure 2).

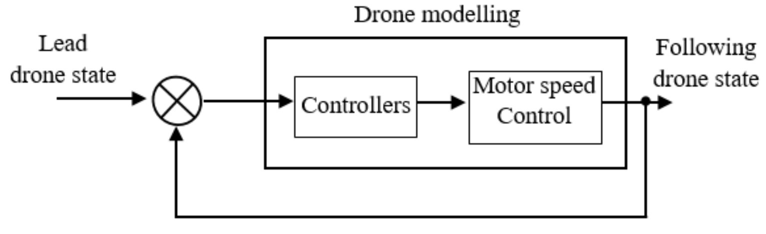


Figure 2: Representation of a general frame for drone-following models

The following formula is the general equation for the drone following models:

$$\ddot{X}_n(t+T) = \lambda \frac{[\dot{X}_n(t)]^p}{[X_{n-1}(t) - X_n(t)]^q} \left[\dot{X}_{n-1}(t) - \dot{X}_n(t)\right]$$

Parameter p stands for speed and parameter q stands for distance headway, *Xn-1(t) - Xn(t)*: relative distance between the two *(n-1)th* and *nth* drones.

If the equation is to be applied in a simulation process, the gap among consecutive recalculations of acceleration, speed, and position should be a small proportion of response time. This requires the storage of a large amount of statistical information. Furthermore, the parameter looks likely to be independent of any identifiable controller or drone features.

The formula was developed by putting limits on the controller and drone's functionality and then using those constraints to compute a speed limit for the fellow drone. It is considered that the pursuing drone's velocity is adjusted by a controller in order for the drone to prevent accidents so when the leading drone is suddenly stopped. This model has two following characteristics: The pursuing drone will speed up if the leading drone speeds up as well. And if the leading drone's speed decreases and since the gap between two drones becomes shorter, the following drone will decelerate as well to keep a steady long distance.

Firstly, the drone-following techniques are effective on the concept of maintaining a safe distance depending on the relative velocity (S.D. models). As a result of this technique, linear models were developed, in which the controller of the pursuing drone adjusts the accelerator to maintain relative speed with the leading drone. The SD models can be used to simulate traffic conditions in a number of different ways. They do, however, have two limitations: the constants used in the drone models are generally derived from real traffic scenarios and sustaining controller quality. Since SD models are having difficulties adjusting for advanced controllers. The Markov chain process is an advanced model which is based on an estimate of the stochastic diffusion process of speed determination. The controllers' inputs receive the appropriate adjustments in velocity from speed variations and relative distance differences between the drones. This method is more comprehensive than the S.D. models due to the Markov chain process can work with extreme situations.

III. RESULTS

The main findings from the simulation analysis of various drone management system applications are presented in this section.

3.1. Experimental result of the difference between real-desired trajectories

In the simulation, drones flying in an urban environment were controlled using a cloud-based method in research studies, which included the physical, cloud, and control aspects. Figure 3 shows the outcome of the experiment. The drone was originally put in a rest position. Once a drone receives a G.C.S. signal, it takes off on a mission to arrive at the waypoints that have been specified. The results reveal that the desired and actual courses mostly coincide with each other. The difference between the two trajectories demonstrates the G.P.S. location since the drone obtains the G.P.S. location data.

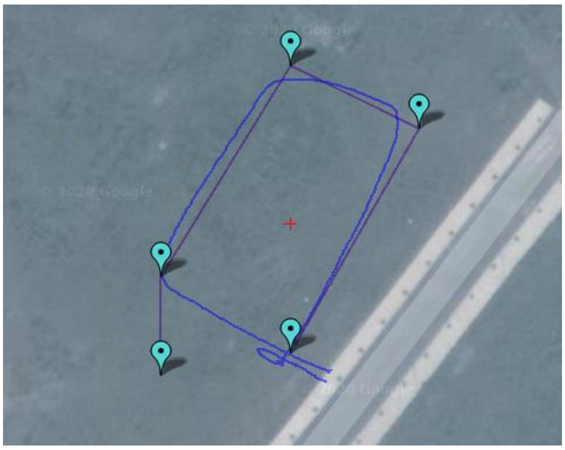


Figure 3: Blue line – real trajectory; Purple line – requested trajectory

3.2. Calculation result of desired orbit landing for a drone

The ideal landing orbit is calculated based on the landing zones, and to provide a drone's landing precisely to the target location. The figures 4 and 5 demonstrate the simulation outcomes for a drone landing in the indicated direction.

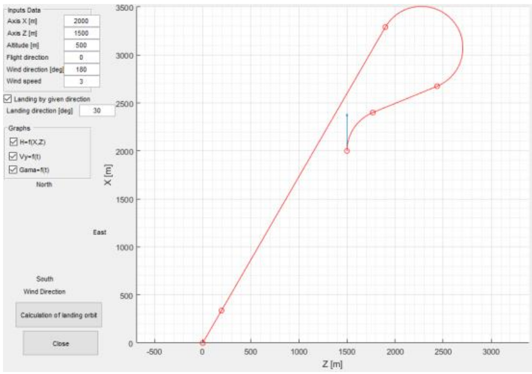


Figure 4: Required landing course of a drone.

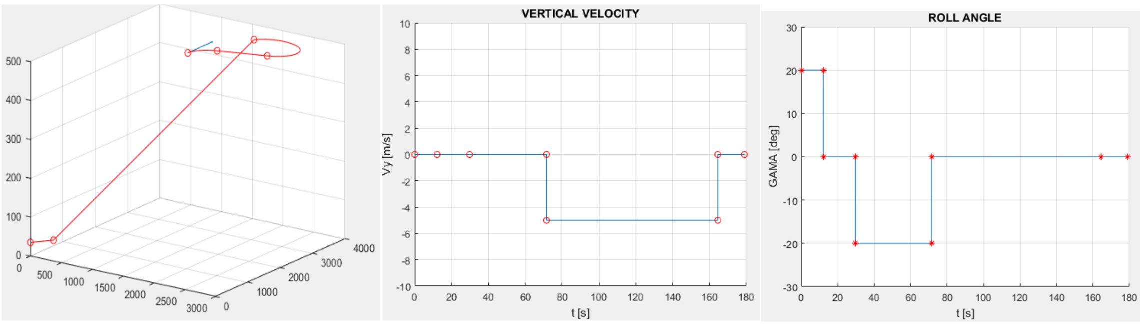
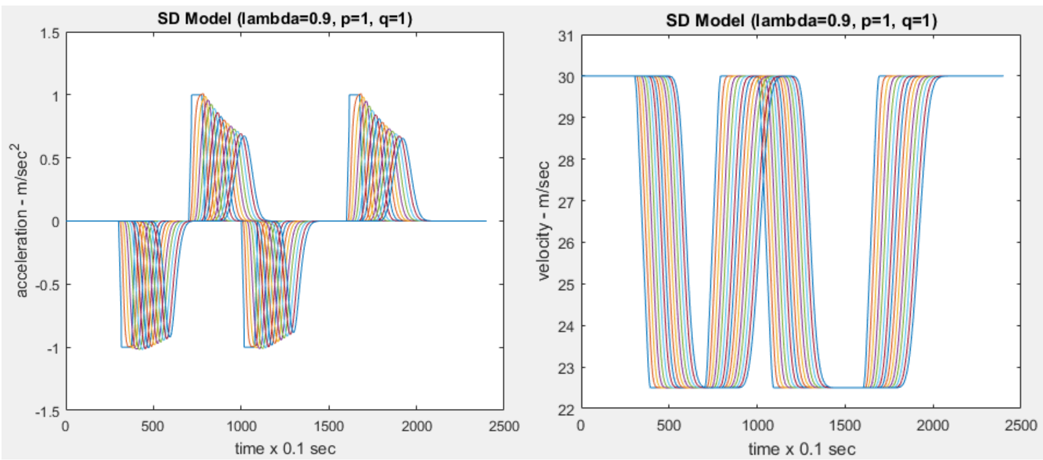


Figure 5: The altitude, vertical velocity, and roll angle change when a UAV gave an instruction to land

3.3. Simulation result of S.D. and Markov models

In general, it can be seen, the S.D. and Markov models are mostly identical (Figure 6). The SD model reacts faster towards changes in patterns of the first drone, however, the dynamics of movement of the preceding drone allow the conditions to stabilize more steadily. The Markov models, on the other hand, consider the factors in the relative distance between the drones (Figure 7). As a result, the leading drone's velocity increases or decreases more than the following drone's velocity. This indicates that variations in relative distances between drones are substantially lower than when S.D. models are used.



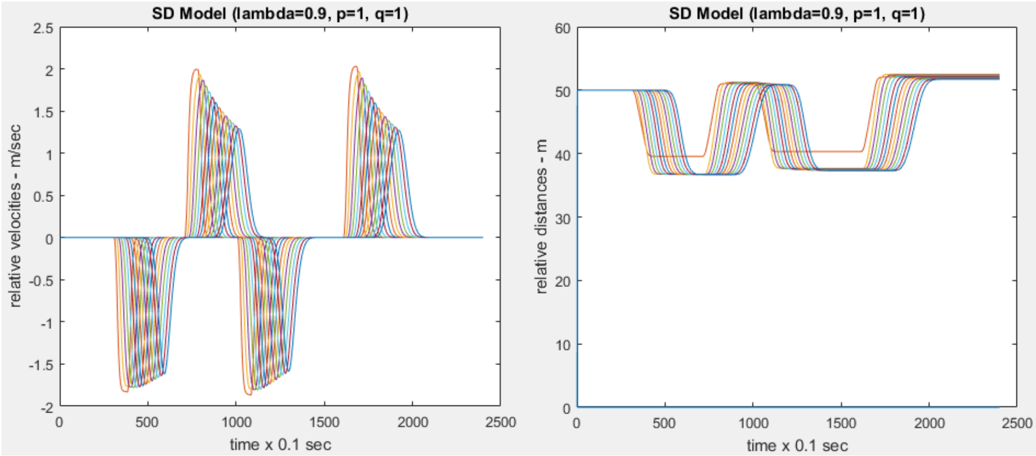


Figure 6: Simulation result of S.D. model

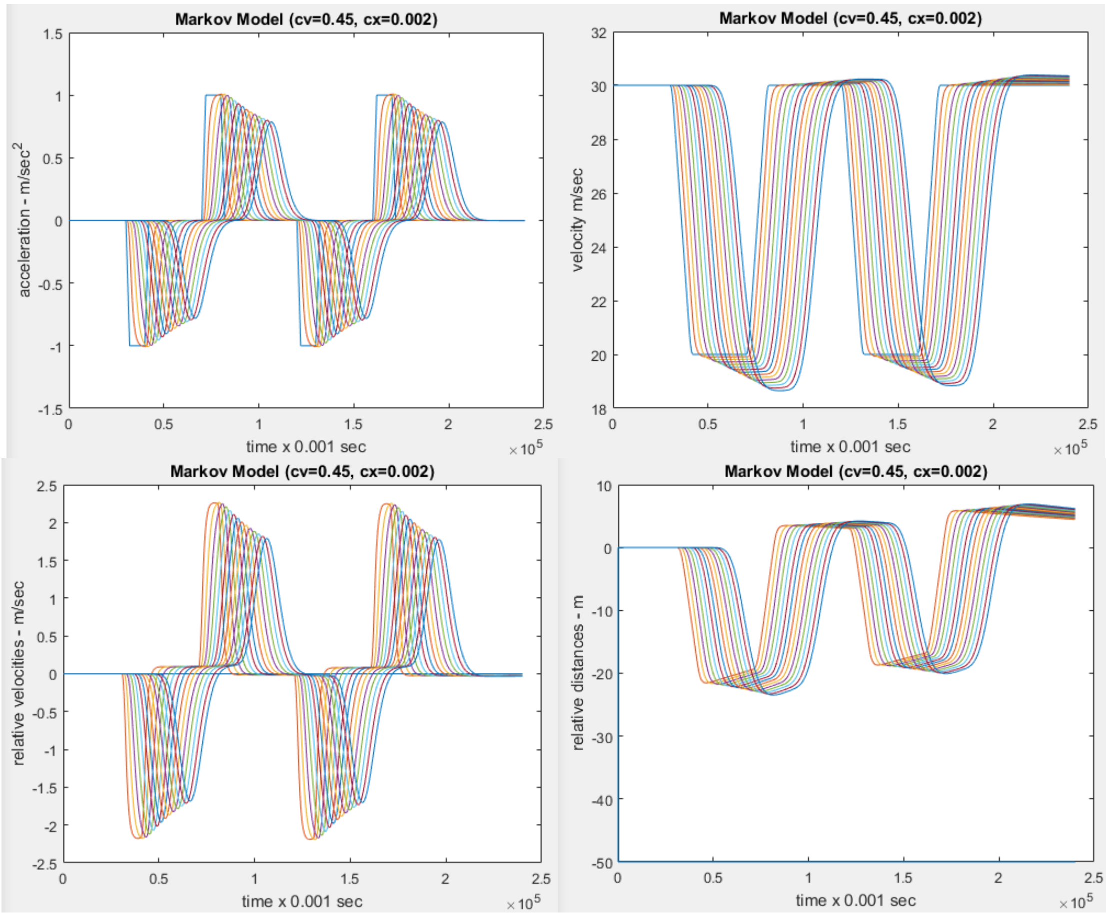


Figure 7: Simulation result of Markov model

The improved Markov model is considered to be more precise in the case of drone movement in significant turbulent air and separated wind flow from infrastructure, and it can be used in areas where positioning problems of G.P.S. have emerged, particularly when making comparisons and collaborations with G.P.S. techniques or ultrasonic sensors, etc.

IV. CONCLUSION

In the future, drones are anticipated to play an important role in almost every field which is essential for humans. For implementing drone usage in the future, drone management systems are needed, and this system should be applied from urban areas to airspace design. Applications of drone control systems need municipalities to embrace large-scale drone operation programs, and drone systems must be secure, reliable, resilient, and sustainable. Thus societies can adopt these new devices more smoothly. Some regulations, designs, and equations for establishing an environment that is safe and secure for aviation purposes of drone operations quality and stability standards are investigated in this study.

There are three major issues that need to be solved about the management of drones:

- Design of flight networks (using G.I.S. systems for data collecting), including a safety net of planned flight paths.
- Defining fundamental legal requirements for traffic flow (like separation requirements) and path of the flight (trajectory).
- Establishing a number of methods and solutions enabling secure flight conditions (like detection and resolutions of the conflict, group flights, drone following models, etc.)

In this research paper, assembling drone management systems including the drone flow methodologies with parametric mathematic models has been suggested. To accomplish this purpose, we first offer parameters of the mathematical model of drones, particularly in quadrotors. Afterward, we presented several methods for designing and operating drone management systems, for instance, obstacle avoidance, the desired trajectory following management, and the required landing trajectory. To add, we proposed G.I.S. usage for data collection and trajectory planning of the drone operations. Finally, one of the key parts of the drone management system, drone following models with S.D. methods and Markov chain process to create safe flying conditions.

REFERENCES

[1]. R. Loh, Y. Bian, and T. Roe, “UAVs in civil airspace: Safety requirements,” IEEE Aerosp. Electron. Syst. Mag., vol. 24, no. 1, pp. 5–17, 2009, doi: 10.1109/MAES.2009.4772749.

[2]. G. W. W., L. J. P., and Z. Dimitrios, “Applications of UAVs in Civil Infrastructure,” J. Infrastruct. Syst., vol. 25, no. 2, p. 4019002, Jun. 2019, doi: 10.1061/(ASCE)IS.1943-555X.0000464.

[3]. P. S. Ramesh and J. V. M. L. Jeyan, “Comparative analysis of the impact of operating parameters on military and civil applications of mini unmanned aerial vehicle (UAV),” in AIP Conference Proceedings, Dec. 2020, vol. 2311, no. 1, p. 30034. doi: 10.1063/5.0033989.

[4]. R. Kellermann, T. Biehle, and L. Fischer, “Drones for parcel and passenger transportation: A literature review,” Transp. Res. Interdiscip. Perspect., vol. 4, p. 100088, Mar. 2020, doi: 10.1016/j.trip.2019.100088.

[5]. J. C. Rosser, V. Vignesh, B. A. Terwilliger, and B. C. Parker, “Surgical and medical applications of drones: A comprehensive review,” J. Soc. Laparoendosc. Surg., vol. 22, no. 3, 2018, doi: 10.4293/JSLS.2018.00018.

[6]. M. R. Dileep, A. V Navaneeth, S. Ullagaddi, and A. Danti, “A Study and Analysis on Various Types of Agricultural Drones and its Applications,” in 2020 Fifth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), 2020, pp. 181–185. doi: 10.1109/ICRCICN50933.2020.9296195.

[7]. A. G. Foina, R. Sengupta, P. Lerchi, Z. Liu, and C. Krainer, “Drones in smart cities: Overcoming barriers through air traffic control research,” in 2015 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED-UAS), 2015, pp. 351–359. doi: 10.1109/RED-UAS.2015.7441027.

[8]. N. D. Dung, “Developing Models for Managing Drones in the Transportation System in Smart Cities,” Electr. Control Commun. Eng., vol. 15, no. 2, pp. 71–78, 2019, doi: doi:10.2478/ecce-2019-0010.

[9]. I. A. Wilson, “Integration of UAS in existing air traffic management systems connotations and consequences,” in 2018 Integrated Communications, Navigation, Surveillance Conference (ICNS), 2018, pp. 2G3-1-2G3-7. doi: 10.1109/ICNSURV.2018.8384851.

[10]. C. Ramee and D. N. Mavris, “Development of a Framework to Compare Low-Altitude Unmanned Air Traffic Management Systems,” Jan. 2021. doi: 10.2514/6.2021-0812.

[11]. W. Lei and C. Li, “On-line aerodynamic identification of quadrotor and its application to tracking control,” IET Control Theory Appl., vol. 11, no. 17, pp. 3097–3106, Nov. 2017, doi: 10.1049/iet-cta.2017.0664.

[12]. J. Wu, G. Liu, and T. Huang, “Noise covariance identification using autocovariance least-squares technique for state estimation of quadrotor,” in 2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2017, pp. 88–93. doi: 10.1109/ICCIS.2017.8274754.

[13]. D. Six, S. Briot, J. Erskine, and A. Chriette, “Identification of the Propeller Coefficients and Dynamic Parameters of a Hovering Quadrotor From Flight Data,” IEEE Robot. Autom. Lett., vol. 5, no. 2, pp. 1063–1070, 2020, doi: 10.1109/LRA.2020.2966393.

[14]. R. Shrestha, I. Oh, and S. Kim, “A Survey on Operation Concept, Advancements, and Challenging Issues of Urban Air Traffic Management,” Front. Futur. Transp., vol. 2, 2021, doi: 10.3389/ffutr.2021.626935.

[15]. S. V Shvetsova and A. V Shvetsov, “Ensuring safety and security in employing drones at airports,” J. Transp. Secur., vol. 14, no. 1, pp. 41–53, 2021, doi: 10.1007/s12198-020-00225-z.

[16]. C. Barrado et al., “U-Space Concept of Operations: A Key Enabler for Opening Airspace to Emerging Low-Altitude Operations,” Aerospace, vol. 7, no. 3, 2020, doi: 10.3390/aerospace7030024.

[17]. J. A. Akintunde, E. A. Adzandeh, and O. O. Fabiyi, “Spatio-temporal pattern of urban growth in Jos Metropolis, Nigeria,” Remote Sens. Appl. Soc. Environ., vol. 4, pp. 44–54, Oct. 2016, doi: 10.1016/j.rsase.2016.04.003.

[18]. M. Farooq and M. Muslim, “Dynamics and forecasting of population growth and urban expansion in Srinagar city - a geospatial approach,” in International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 2014, vol. XL–8, no. 1, pp. 709–716. doi: 10.5194/isprsarchives-XL-8-709-2014.

[19]. M. A. Dereli, M. A. Ugur, N. Polat, and M. Yalcin, “Spatio-temporal analysis of urban expansion using remote sensing data,” in International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM, 2017, vol. 17, no. 23, pp. 239–246. doi: 10.5593/sgem2017/23/S10.029.

[20]. C. Kivilcim and Z. Duran, “Impact of rapid urbanization on the morphology of historical Istanbul: Üsküdar district case study,” in The 17th International Symposium on Environmental Pollution and its Ompact on Life in the Mediterranean Region (MESAEP), 2013, pp. 14–18.

[21]. N. Kaya, Ö. Turan, T. H. Karakoç, and A. Midilli, "Parametric study of exergetic sustainability performances of a high altitude long endurance unmanned air vehicle using hydrogen fuel," Int. J. Hydrogen Energy, vol. 41, no. 19, pp. 8323–8336, 2016, doi: 10.1016/j.ijhydene.2015.09.007.

[22]. M. Herold, J. Scepan, and K. C. Clarke, "The use of remote sensing and landscape metrics to describe structures and changes in urban land uses," Environ. Plan. A Econ. Sp., vol. 34, no. 8, pp. 1443–1458, Aug. 2002, doi: 10.1068/A3496.

[23]. T. McPhearson et al., "Advancing Urban Ecology toward a Science of Cities," Bioscience, vol. 66, no. 3, pp. 198–212, Feb. 2016, doi: 10.1093/biosci/biw002.

[24]. N. Tohidi and R. B. Rustamov, "A Review of the Machine Learning in GIS for Megacities Application," in Geographic Information Systems in Geospatial Intelligence, R. B. Rustamov, Ed. IntechOpen, 2020, pp. 29–53.