Mathematical and Machine Learning Based Methods for UAV Simulation: A Systematic Literature Review

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ABSTRACT

Unmanned aerial vehicles (UAVs), frequently called drones, have become highly useful assets in various industries such as surveillance, transportation, and agriculture. Understanding and evaluating drone behavior is difficult because of the intricate interplay of factors such as velocity, altitude, remote controller input and flight path. Therefore, proficient, and knowledgeable workers are required for efficient drone operations. It is essential to have strong training programs for drone pilots to satisfy these expectations. The inclusion of drone simulators is a vital component of these training programs. Drone dynamics simulations are of great importance in several industries since they allow researchers to design and evaluate drones in intricate situations that would otherwise be dangerous or impractical. This paper examines different drone dynamic models based on principles of Newtonian fluid dynamics. The focus of this study is specifically on fundamental elements such as force, gravity, propeller characteristics, and air density. Moreover, this research examines the utilization of machine learning approaches for simulating drone dynamics. This study analyzes different simulation models and conducts a comparison to find areas of research that have not been addressed. After identifying these gaps, the research examines potential ways to address the drawbacks of current simulation models in the future. This research aims to offer valuable insights to future academics who are interested in constructing customized drone simulators. This work works as a core resource, directing the building of customized drone simulators for different uses.

Keywords-- Machine Learning, Drone, Simulation, UAV, Newtonian and Fluid Dynamics

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) become popular over the past two decades because of their numerous uses in surveillance, disaster management [1], pollution monitoring, cinematography, archaeology [2], pizza delivery, and military reconnaissance [3]. The precise date of the initial successful UAV flight remains unknown. However, many sources assert that the development of UAVs may be traced back to 1849 when the Austrians deployed a fleet of 200 unmanned balloons in an attacking maneuver targeting the city of Venice [4]. The primary causes of this include the high maneuverability designed into UAVs, their capacity for vertical takeoff and landing (VTOL), and their stable hovering abilities [5].

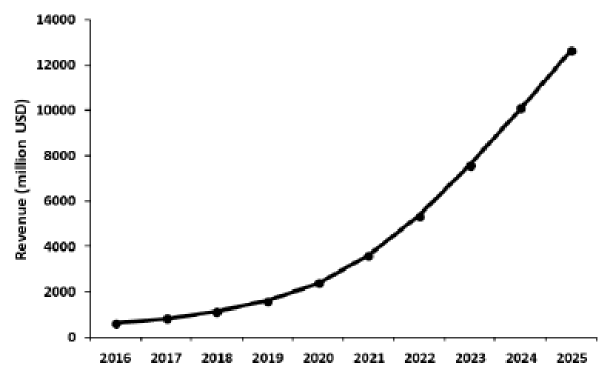

Figure 1: Global revenue generated by commercial UAVs from 2016 to 2025

These versatile unmanned aerial vehicles navigate without human operators, revolutionizing various sectors by offering aerial viewpoints in risky or inaccessible scenarios. Drones are very useful for making movies, protecting the environment, and helping people after a disaster because they are very efficient and new. They make armed reconnaissance and surveillance better, which changes how wars are fought today. The invention of drones started a new era that changed what hovering technology can do [6]. The UAV business has grown very quickly over the last five years. Fig. 1 shows forecasted revenue through 2025 as well as the global commercial UAV revenue from 2016 to 2019 [6].

As drone technology improves, there is a huge need for skilled and knowledgeable workers. For this technology to be used effectively, the workforce must possess both theoretical knowledge and practical abilities.

Comprehensive training programs are now necessary to achieve these demands.

The use of drone simulators is a key component of this training. These simulation programs provide a safe setting for aspiring drone pilots to improve their abilities and get comfortable with the specifics of flying drones. It is impossible to overstate the value of drone simulation, particularly since some drone activities are very dangerous. Before real-world deployment, professionals can evaluate and improve their abilities by simulating drone operations. One essential element that sticks out is drone simulation, which offers drone pilots significant training and hands-on experience. Additionally, by using simulators, costs and training durations can be minimized, and the risks and damages associated with improper operations can be decreased. There exist numerous justifications for employing simulation instead of conducting a real-world experiment on a given system. Five primary factors contribute to this phenomenon.

- Conducting experiments on actual systems is too costly.
- It poses significant risks. Before executing the maneuver in the aircraft, the pilot has the opportunity to rehearse a perilous maneuver.

Figure 2: Early Manual Flight Training Devices

- The system is currently non-existent, and the model will serve as a prototype for evaluation and testing purposes.
- Variables that are not accessible in the actual system can be viewed in a simulation.
- It is straightforward to utilize and modify models, as well as adjust parameters and conduct fresh simulations. System design optimization allows for the evaluation of numerous variants.

Due to these factors, drone simulations are crucial in numerous fields. The following are the main points presented in this review of literature.

- This study aims to analyze the historical progression of drone simulators, providing readers with a comprehensive understanding of the origins of the unmanned aerial vehicle (UAV) simulation industry and its subsequent growth in recent times.
- Conduct a comprehensive examination of numerous simulators across diverse categories, accompanied by a comparison assessment.
- Identifies the limitations that are common in current drone simulators.
- Finally, This study identifies research gaps and future work.

II. BACKGROUND STUDY

In 1910, aviators were trained using the first flight simulator, which functioned regardless of wind conditions. Figure 2 illustrates the first flight simulator whose structure consisted of two parts of a barrel, which were manually assembled and manipulated by a pilot situated in the upper portion of the barrel . Also, the First World War pushed people to make better machines for teaching pilots to fly. Control and recording equipment for electricity were put in these models. Subsequently, these flight simulators achieved significant improvements to the extent that they were designed to accurately replicate the response of a real aircraft to the pilot's control inputs. This was made possible by installing electrical and mechanical equipment. Between 1927 and 1930, Edwin Link developed one of the most famous and successful flight simulators. At that time, it was thought to be the best and most innovative way to train, and it became the most famous and preferred way to train pilots during World War II. During World War II, electronic models became popular because computers could now solve the equations for flight dynamics. During the 1950s, Curtiss Wright made the first full simulator for an airline called Pan America. This simulator, which has sounds and images of planes, was bought by US Airlines for $3 million. It is thought to be one of the first modern flight simulators. In the 1960s, movements along the pitch, roll, and yaw axes were added to simulators. In the 1970s, very simple computer graphics models with a single moving white dot on a black background came out. Over time, the screens changed into more detailed and completely dynamic ones. There are two primary purposes of these drone simulators.

- One purpose is to assist individuals who are passionate about drones in honing their skills in First Person View (FPV) flying.
- On the other hand, enhance the control and maneuverability of drones in different environmental conditions.

UAV simulators can be classified according to their compatibility with outdoor or indoor environments, their application in research or entertainment, their use for single UAVs or networks of UAVs, and whether they are completely software/hardware or hybrid systems .

Simulators are vital tools for drone enthusiasts, design engineers, and researchers, as they fulfill a multitude of functions. One such use is to facilitate the training and improvement of videography abilities, particularly in the context of FPV. Furthermore, considering the specific field of application, the inclusion of graphic detail in a simulator is vital to achieve a truly authentic experience and ensure the technical integrity of the aerodynamic design.

There are two primary methods for simulating drone dynamics: traditional techniques that depend on physics and mathematics, and modern AI-based technology. Traditional approaches are based on established physical and mathematical principles, offering a solid foundation but frequently requiring exact input parameters and assumptions. On the other hand, AI-based simulations make use of modern techniques like deep learning and reinforcement learning, which allow the simulations to pick up complex patterns and adjust to a variety of strange and varied situations. The article discusses numerous simulation models based on both traditional approaches and AI-based technology with comparison.

When developing a simulator, the designers and engineers need to consider the aerodynamic characteristics, three-dimensional flight capabilities, and network communication aspects of drones. An effective UAV simulator requires the addition of several key attributes. User-friendliness, compatibility with commonly available technology, reduced complexity, and an easy-to-use graphical user interface (GUI) are a few of them. List comprehensive outline of crucial prerequisites for an effective UAV simulator is presented below .

- Flight dynamics model: understanding the aerodynamic forces experienced during flight is essential for optimizing aircraft design and enabling precise pilot control. Designers of flight simulators can utilize aerodynamic equations to represent the behavior of drones.
- System model: The dependability of a drone simulator is contingent upon a precise mathematical depiction of the UAV system. Models can be classified into two categories: those that are developed through a comprehensive understanding of the system and those that are obtained from real-world data. The goal is to replicate the actions of an actual UAV.
- Graphical model: UAVs use restricted color schemes, vector graphics, alphanumeric text, and symbols in their graphical representations. Displays should have a minimum 20-second refresh rate and use 2D graphics methods. Cartesian coordinates are used, with differences depending on the display mode.
- Control system: Drone simulators view control systems as mathematical transfer functions. Therefore, the designer of the simulator must incorporate these transfer functions in an algorithmic style to guarantee precise modeling of the input-output relationship of the system .
- Flight route identification: The aircraft's navigation system facilitates the determination of both present and future positions for its users. The navigation system collaborates with several additional subsystems to facilitate various functionalities, including the identification of flight routes, avoidance of collisions, planning of optimal paths, and assignment of air corridors.

III. SIMULATION MODELS

In this section, explore the different types of simulation models based on mathematical equations and machine learning models.

3.1 Multi-Rotor Flight Simulator

UAV simulation method using numerical techniques was introduced by David Orbea and Jessica Moposita. They include numerical approximations in their mathematical model, which includes several Single Input Single Output (SISO) systems. These systems have relationships between altitude, pitch, roll, and yaw angles as input parameters and yaw speed and x, y, and z-axis speeds as output parameters. Fig. 3 shows these aircraft's angles and orientations. Identifying the complicated relationships between the aircraft's speed on the X-axis and the pitch angle, its speed on the Y-axis and the roll angle, and its speed on the Z-axis and the yaw angle are the main objectives of this mathematical analysis. These connections are defined with the help of precise mathematical transfer functions. Data collection involved executing a pre-planned flight, where the aircraft followed a specific low-speed rectangular path. This methodological decision was introduced to reduce the computing calculation that comes with figuring out these complex transfer functions.

3.2 Quadrotor Flight Simulator

Using the Newton-Euler method, Fernando H.C.T.E and De Zoysa M.D.C. have provided an approach for simulating quadrotor dynamics [5]. The model predicts the effects of the forces and torques generated by the four propellers on the quadrotor motion. Four control variables were chosen for this method to match the four fundamental movements of roll, pitch, yaw, and vertical movement. A global position perspective is provided by the Earth's reference frame, which is fixed to the Earth. The quadrotor is connected to the body's reference frame, which describes the body's internal motion.

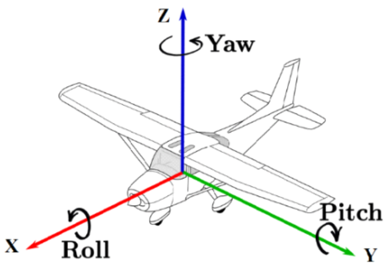

Figure 3: Pitch, yaw and roll angles of an aircraft

Kinematics of a rigid body is given by,

$$i=J\theta v \qquad (1)$$

where i and v are the generalized velocity vectors regarding the Earth's frame and the body frame, respectively. is the generalized matrix that transfers velocities of the body frame to Earth's frame. The dynamics of the quadrotor are given by the following Newton-Euler equation.

$$\begin{bmatrix} mI_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & I \end{bmatrix}\begin{bmatrix} \dot{V}^B \\ \dot{\omega}^B \end{bmatrix} + \begin{bmatrix} \omega^B \times (mV^B) \\ \omega^B \times (I\omega^B) \end{bmatrix} = \begin{bmatrix} F^B \\ \tau^B \end{bmatrix} \qquad (2)$$

Where m is the mass of the quadrotor, is the inertia tensor, is the 3x3 unity matrix, and are the angular and linear velocities of the quadrotor concerning the body frame. and are the force and torque vectors.

Using MATLAB Simulink, a quadrotor simulator was created based on the model, allowing for the development and testing of several control algorithms. However, the gyroscopic effects, wind resistance, propeller dynamics, and cross-coupling effects of the spinning motors (one type of movement might affect its other movements) were not considered in this work.

3.3 Hexagon Flight Simulator

Interactions take place among the three primary constituents of this simulator, namely the mathematical model software, the GUI based on Lab view, and the rendering engine. To effectively present the flight information, it is necessary to utilize a configuration consisting of three LCDs. These monitors will be allocated for the display of the flight data, the virtual cockpit, and the real-time flight parameters updating. The major components of the system are referred to as the models and the engine. The models are created using Fortran (Programming Language) and consist of three sub-modules:

- Airplane dynamics: The field of airplane dynamics includes the study of the movement and characteristics of an aircraft as it reacts to outside factors, including aerodynamic forces, thrust, and gravitational forces.
- Propulsion system: The choice of the propulsion system for a given trip is contingent upon several criteria, including the dimensions of the aircraft, the distance it must travel, the required velocity, and considerations of efficiency.
- Atmospheric system: The atmospheric system employs a graphics engine that is created using the C/C++ programming language. The software provides a diverse selection of camera features that enable the virtual car to rotate within the simulation. Operators must have a thorough understanding of Micro Aerial Vehicles (MAVs) due to their complex maneuverability. To streamline this process, the hexagon integrates both a joystick and a radio controller (RC) to provide improved control. The User Interface of the RC simulator has been improved to integrate this feature, hence boosting its realism and usability. The pilot can assess various autopilot settings, including the proportional-integral-derivative (PID) gains, to improve the platform's performance in real-world situations. It is possible to adjust the mission settings during the simulation, starting from a simple scenario. Fig. 4 illustrates the hardware of the hexagon Flight Simulator.

Figure 4: Hexagon Flight Simulator

3.4 AirSim Simulator

AirSim is a drone simulator operating system (O/S) created by Microsoft's Aerial Informatics and Robotics (AIR) team. The main objective of this tool is to function as a significant resource for conducting AI research, particularly in the areas of deep learning, computer vision, and reinforcement learning algorithms. The simulator is specifically tailored to accommodate a diverse array of autonomous drones. Originally, the extent of this notion was limited to the simulation of quadcopters. The Autonomous Intelligence Robotics (AIR) effort seeks to integrate commonly used aerial robotic models. The utilization of this simulator has the potential to provide training data that can be employed in the construction of machine learning (ML) models.

AirSim consists of various fundamental components, which include an environment model, a vehicle model, a physics engine, sensor models, an API layer, a rendering interface, and an interface layer which are shown in Fig. 5. The flight controller receives the desired state and sensor data as inputs, computes the overall estimation of the present state, and generates the required actuator control signals to attain the intended state. The user-specified roll, pitch, and yaw angles define the desired condition for quadrotors. The flight controller utilizes data from the accelerometer and gyroscope to evaluate the present angles and ascertain the motor impulses required to attain the target angles. The simulation enables the transfer of sensor data to the flight controller, which generates commands for the actuators of the vehicle model in the simulator. The vehicle model is specifically engineered to compute the forces and torques produced by the simulated actuators. In the field of quadrotors, the propellers have the dual function of generating both thrust and torques. The calculated motor voltages determine these forces. Likewise, it is plausible that supplementary forces, such as drag, friction, and gravity, might also exist. The forces act as an input to the physics engine, facilitating the calculation of the resulting kinematic state of objects in the simulation. When analyzing the kinematic state of entities in the simulator sensor model, it is essential to consider several environmental parameters, including gravity, air density, air pressure, magnetic field, and GPS position.

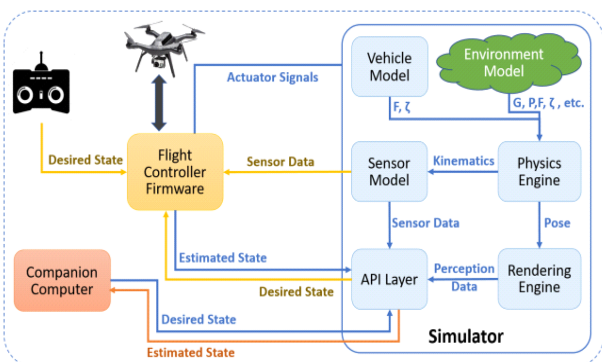

Figure 5: AirSim Architecture

The system can efficiently handle a substantial amount of data produced by the sensors, while also being capable of identifying instances of collisions. The purpose of the API layer is to insulate the companion computer from discerning whether it is engaged in a simulation or a real-world experiment. This procedure facilitates the development of algorithms within the simulator, which may subsequently be applied to an actual vehicle without requiring significant alterations [15].

3.5 DJI Flight Simulator

The DJI Flight Simulator is another option for simulating commercial drones. This software simulator lets users mimic the actions of several DJI-branded UAVs and controllers. The weather and sunshine settings can be customized, and the simulator offers a variety of 3D scenarios [16]. Using DJI's advanced flight control technology, DJI Flight Simulator is a professional pilot training program that simulates the feeling of really being in the air. It supports a large selection of DJI drones and is designed for business users. However, this simulator is not flexible for addressing specific research and development. The primary problem with DJI Flight Simulators is their proprietary software, which means that the remote operation devices and simulated UAVs have limitations and cannot be expanded [17]. Furthermore, it is a very difficult challenge to simulate custom-built drones with these generalized drone dynamics.

3.6 Simulator with Reinforcement Learning

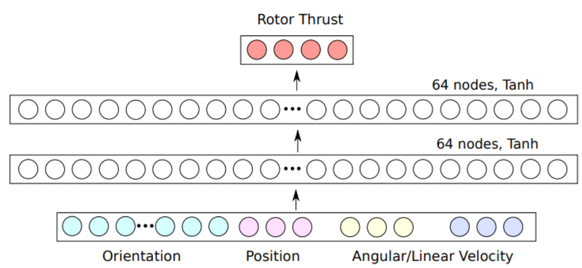

Figure 6: Neural networks of Quadrotor

The primary objective of this study is to develop a methodology for controlling the movements of a quadrotor, which is a specific form of UAV that includes four rotors, by using a neural network that has been trained using reinforcement learning methodologies . The objective of the researchers is to develop a control system in which a neural network is trained to directly establish a correlation between the quadrotor's state and the corresponding actuator commands. This approach aims to eliminate the requirement of a pre-established control structure during the training process. The developed algorithm consists of 2 hidden layers with 64 tanh nodes. The structures are illustrated in Fig. 7. The author's technique is distinguished by the introduction of a novel learning algorithm, characterized as conservative yet stable, and specifically designed for complex tasks. The authors contend that their approach demonstrates greater applicability in the realm of quadrotor control when compared to previous algorithms. The efficacy of the trained neural network is showcased by the researchers through its application in both simulated environments and practical trials with a physical quadrotor.

The research emphasizes several notable achievements. The primary objective of this research is to enhance the domain of quadrotor control through the introduction of an innovative neural network-based methodology that demonstrates efficacy and efficiency in both simulated and real-world contexts. The scope of this experiment is constrained to a confined space with dimensions of approximately 2m x 2m x2m for creating a controlled environment.

3.7 Simulation with Eight Maneuvering Patten

The data collection technique involved the utilization of the Figure eight maneuvering pattern and the construction of a machine learning-based drone dynamic model. The data gathered in this study relates to the eight-maneuvering pattern because of its wide use in different activities all over the domains of aviation, maritime, and ground vehicle operations . In this method, an experienced pilot was chosen to do several figure-eight maneuvers using a DJI Phantom drone. The maneuvering testing was carried out in a tranquil environment with minimal wind conditions. Fig. 7 illustrates the actual aerial view of a sample drone pilot drill, which has a shape like a figure of eight. The track's actual dimensions

are a width of 24 m and a length of 60 m. The recorded data can be classified into two primary categories as follows:

- The drone operator uses the drone Radio Controller (RC) to input commands, such as throttle and rudder values, which determine the drone's location and orientation adjustments.
- The drone's position and orientation are dynamic and vary over time, as do other pertinent sensor readings such as battery level, accelerations, and velocities.

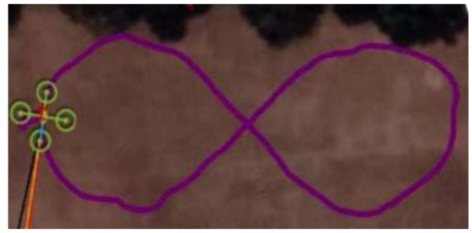

Figure 7: Actual aerial view of a sample drone pilot drill

A machine-learning model was constructed utilizing the time stamp, radio controller orders, battery voltage, position, and orientation data of the drone. The model that has been created is built upon the principles of based on regression and multiple target variables concept. The machine-learning model was provided with a data set of recorded radio controller inputs from a figure of eight trials. The model then predicted the position and orientation of the drone based on this data. The observed pattern and the expected pattern are considered to have sufficient overall shape similarity. However, this approach was inefficient in addressing accuracy issues caused by data preparation procedures, the little impact of wind, and the choice of machine learning technique.

IV. COMPARISON OF SIMULATION MODELS

Table I: displays the model type and framework utilized for development and the limitations of each simulation.

Table 1: Comparison of Models

Simulator	Model Type	Framework	Limitations
Multi-Rotor Flight Simulator	Mathematical transfer function	MavLink Telemetry	• Data collection was conducted using a rectangular flight path that did not imitate complex drone movements. • The wind effect is assumed to be constant.
Quadrotor Flight Simulator	Newton-Euler method	MATLAB Simulink	• Employed multiple model parameters to forecast the dynamics of the drone, such as its form and weight.
Hexagon Flight Simulator	proportional-integral-derivative	-	• Simulators cannot completely substitute real-world experience. • The accuracy of a system relies on various elements such as the stability of the network and integration of third-party software.
AirSim Simulator	Machine Learning Model	• Unreal Engine • Computer Vision and AI Libraries	• Simulations were limited to quadcopters. • require robust hardware for optimal performance.
DJI Flight Simulator	Mathematical models	• Unity 3D • DJI SDK	• Simulate only DJI brand drones. • Commercialized simulator. • Running a realistic flight simulator requires a powerful computer.

Simulator with Reinforcement Learning	Reinforcement Learning	• TensorFlow	• Data Collection involves small environments. • Mismatch between simulated and real-world dynamics
Simulation with Eight Maneuvering Patten	Multi-output regression model	• MATLAB • AI Libraries	• Model has poor accuracy. • Unbale to predict complex dynamics

V. FUTURE RESEARCH DIRECTION

Due to the complexity of various model factors, commercial simulators like DJI, and the lack of generic simulation models, it's difficult to evaluate the essential model parameters for simulating a custom-made drone. Developing a machine learning-driven dynamic drone simulation model to replicate customized drones will offer a direct approach to overcoming these restrictions in the future.

VI. CONCLUSION

UAV simulators consist of various categories, each carefully designed with specific goals and features that cater to target audiences. These technologies are employed in academic and research settings, where universities and research groups apply them to improve UAV simulations, gain crucial insights into drone technology, and contribute to the advancement of new UAV protocols. This research provides a comprehensive analysis of existing drone simulators, focusing particularly on their utilization of Mathematical and machine-learning techniques. Furthermore, the paper includes a thorough analysis of the inherent limitations of these approaches and their impact on simulation methodologies. Future research has focused on developing a customized drone simulator capable of simulating the dynamics of any drone.

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