A Comparative Evaluation Framework with Quantification for UAV Simulation Platforms

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Abstract: The significance of Unmanned Aerial Vehicles (UAV) is quite high in precision agriculture, disaster response, surveillance system, logistic etc. However, there is a need for a reliable simulation platform for studying UAV as there are safety constraints, environmental uncertainty, and increased cost for real-world testing. The current state of UAV simulators is witnessing lack of benchmarks, minimal physics fidelity, integration of Artificial Intelligence (AI), restricted interoperability etc. Therefore, this study chooses to investigate some prominent UAV simulation tools viz. MATLAB UAV Toolbox, Gazebo, AirSim, X-Plane, FlightGear, JMAVSim, and OpenUAV adopting a multi-stage framework of evaluation. The quantitative outcome of the study finds that efficient support of hardware-in-the loop is facilitated by MATLAB UAV Tools and higher scalability towards swarm operation is supported by OpenUAV.

Keywords: Component; UAV; Comparative Study; Artificial Intelligence; Platforms, Tools; Simulation

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Introduction

There has been a rapid evolution of Unmanned Aerial Vehicles (UAV) towards versatile tools from experimental prototypes. They are usually applied to logistics, environmental monitoring, surveillance, disaster response, and precision agriculture. Their significance in industrial applications and academic research work is mainly boosted due to their capability towards operating on adverse environments, operating on inaccessible areas, aggregating real-time data, and carrying out autonomous missions [1][2]. However, there has been growing concern of challenges mainly due to high operational cost, environment unpredictability, regulatory constraints, safety risk etc [3]. The current state of UAV simulation tools suffer from inferior interoperability states, restricted integration of Artificial Intelligence (AL) or Machine Learning (ML), absence of any standardized benchmarks, significantly limited physics fidelity [4][5]. This challenge acts as potential impediment for any researchers towards validating and testing controls of UAV, perception system, or autonomy towards reproducibility. One approach towards understanding this problem is to carry out a comparative study towards the existing state of UAV platforms or simulation tools. Various key parameters like cost, compatibility of intelligent systems, supportability towards hardware-in-the-loop, sensor modeling, etc. can be considered towards realizing the trade-off between varied states of simulation-oriented analysis [6]-[8]. This eventually contributes towards gap identification in existing solutions. The prime problems that demand significant attention are directed towards lack of an integrated framework towards performing a comprehensive set of operations that is much anticipated for any UAV platforms. Some of the notable problems are related to inaccurate models of flight dynamics. The fidelity is potentially reduced due to environment effects (e.g. wind gust, turbulence, etc.), propulsion, aerodynamics that are simplified by existing UAV simulation tools. They are also characterized by highly restricted sensor simulation. There is a lack of failure modelling along with consideration of delay, realistic noise in current simulation tools towards radar, cameras, LiDAR, and GPS. The effect of payload (viz. delivery mechanism, weapon system, camera gimbals) for studying energy consumptions and dynamics are inadequately represented. There are bigger sets of challenges towards networking and communication systems in existing UAV platforms e.g., lack of cross-layer simulation, oversimplified network modelling. Hence, existing simulation tools of UAV suffer from unrealistic operator models, zero threat modelling, lack of benchmarks, computational limits, closed tools usage, idealized communication, weak multi-agent supports, and inferior sensor models [9]-[10].

The aim of the proposed study is towards carrying out a systemic evaluation towards varied design platforms of UAV in the form of comparative study. The contribution of proposed study are as follows: i) the presented work carried out comparative analysis of different simulation tool used in studying UAV that are frequently adopted, ii) a quantitative evaluation framework is designed that considers assessing multiple practical parameters towards gauging effectiveness of UAV simulation tools, iii) the study generates numerical outcomes for exhibiting strength and weakness and thereby facilitating better decision making for upcoming researchers, and iv) different from existing review, the study gives more emphasis to perform quantitative study on UAV tools for measuring practical side of applicability. The organization of this manuscript is as follows: Section II presents discussion of existing literature, while Section III presents discussion towards proposed research methodology. The accomplished result is illustrated in Section IV while conclusion is briefed in Section V.

Related work

This section presents a summary of prime contributions that correspond to the proposed study model towards analyzing UAV platforms. In the perspective of studies towards *UAV platforms and simulators*, the work carried out by Chen et al. [11] have discussed open-sourced simulation platforms towards multi-copters swarms of UAV viz. USARSim, MORSE, MRDS, ARGoS, CoppeliaSim, Gazebo, and Webots. The assessment is done with multiple evaluation dimensions to find Webot much applicable in swarm simulation. Nikolaiev and Novotarskyi [12] have also carried out comparative assessment of UAV simulators especially focusing on multi-agent use cases and environment dynamics. The study highlights the trade-off between standardization and feature diversity. Perez-Segui et al. [13] have bridged the gap between real autonomous UAV flights and simulators emphasizing on practical transition to real flight from simulation and fidelity gap. Pal et al. [14] have studied broader capabilities of UAV that involve navigation, sensing, green computing, AI/ML, etc. giving more information towards simulation tools. Chan et al. [15] have reviewed practices and challenges encountered by UAV simulators adopting a reinforcement learning approach. Some notable and recent studies towards simulation platforms and methodologies have been also carried out by Patil et al. [16], Borges et al. [17], Capek et al. [18] and Jung et al. [19]. In the perspective of studies towards *feature modelling*, Boshoff et al. [20] have studied the performance towards UAV used for industrial applications. The authors have discussed the applicability of certain metrics e.g., position overshoot, pose accuracy, path accuracy towards better performance. Hansen et al. [21] have presented a study towards identification and modelling of UAV with smaller and fixed wings adopting evaluated aerodynamic angles with 6 degrees of freedom. The work carried out by Lin et al. [22] have presented a semi-physical platform of simulation with hardware-in-loop towards verification of real-flight, capturing sensor fidelity, and optical-flow navigation. Aliane et al. [23] have evaluated open-source autopilots in UAVs along with studying their integration with simulators and hardware incorporated within the framework. In perspective of studies towards *experimental evaluations*, Ye et al. [24] have developed a task allocation algorithm that works both online and offline for multiple UAVs. The study has illustrated task allocation along with assessing latency and computational load in settings of sensor networks. Alqudsi and Makaraci [25] have investigated UAV swarms perspectives towards determining the gaps associated with UAV swarms.

The identified research gaps are: i) current UAV simulators mainly emphasize on particular factor e.g. autonomy or communication, without unifying multiple operations into one integrated platform, ii) Existing platforms also lacks sensor modeling and high-fidelity physics which obstruct the precise representation in real operations of UAV, iii) there are potential scalability issues limiting UAV operation to complex scenarios, and iv) there is no benchmark standardized with efficient evaluation metrics towards simplifying validation and comparison. The next section highlights the solution to mitigate the identified issue.

Research Methodology

The key agenda of the adopted multi-stage methodology is focused towards developing a highly comprehensive comparative assessment towards design platforms of UAV. An architecture is designated for this purpose (as shown in Fig.1) towards unifying multiple entities e.g. analytical synthesis, cross-platform benchmarking, experimental evaluation, system feature extraction etc. The study has considered both qualitative and quantitative evaluation methods by considering practical evaluation with literature-oriented analysis on a defined environment of simulation. The notion for each framework component is towards acquiring very unique dimensions towards gauging the capabilities of UAV simulation that involves hardware interoperability, AI/ML integration, sensor modeling, physics fidelity, etc.

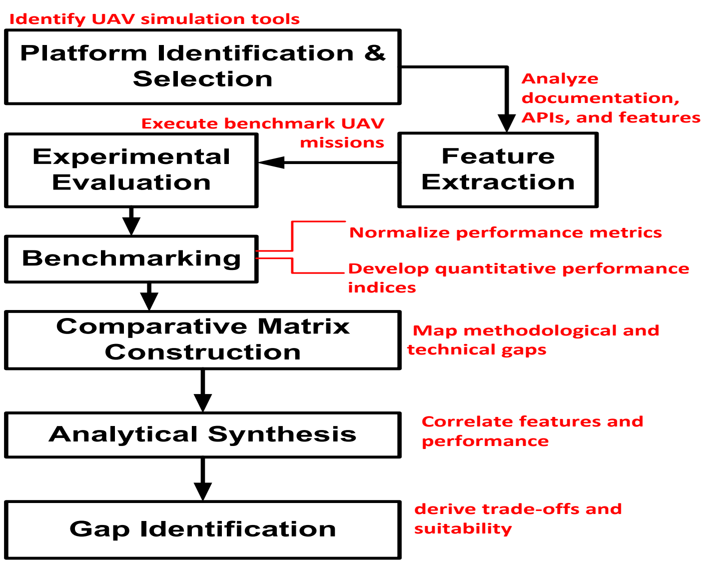


Figure 1. Architecture of Proposed Model

A. Platform Identification & Selection

This module performs identification followed by opting for a representative scenario of UAV design platforms encapsulating a higher scope of application domain, licensing model, and technical capabilities. This module initiates by performing extensive review of literature towards simulation tools for UAV. Further, three classes of different platforms were selected for studying e.g. Cloud-based platform (*OpenUAV*), open-source platform (*JMAVSim*, *AirSim*, *FlightGear*, *Gazebo*), and commercial platform (*X-Plane*, MATLAB UAV Toolbox). The novelty of this module resides in the taxonomy-driven process of selection towards providing balanced representation over research domains and software paradigm.

B. Feature Extraction

The ideation of this module is towards constructing a standardized taxonomy of UAV features for facilitating comparative study. The official documentation, user communities, and APIs for each simulation tool are analyzed followed by categorizing them under multiple dimensions e.g., sensor modeling, physics fidelity, scenario flexibility, etc. Finally, multi-layer taxonomy is generated from mapped extracted features exhibiting usability, extensibility, and simulation depth. The novelty of this module is that it formalizes multi-dimensional evaluation taxonomy oriented reusable framework towards benchmarking and any future comparative studies.

C. Experimental Evaluation

This module is responsible for studying the opted platforms of UAV empirically via controlled research environment towards mimicking missions of representation UAV. For this purpose, the scenarios of benchmark simulation (viz. obstacle avoidance, swarm formation, waypoint navigation, etc.) is designed. This is followed by implementing UAV missions and models over all platforms followed by aggregating performance data (e.g. accuracy of sensor outcome, stability of simulation time-step, processing load, etc.). The novelty of this module is that it combines cross-platform experimentation with an empirical approach adopting standardized missions. This facilitates quantified findings contributing towards reliable performance-based comparative study.

D. Benchmarking

This module performs normalization and quantification of the UAV platform performance considering a specific set of assessment metrics. The benchmark metrics (viz. delay of control loop, sensor latency, consistency of frame rate, etc.) have been developed followed by adopting statistical analysis towards assessing variance and repeatability over simulation rounds. Finally, the scores were normalized for deriving performance indices specific to platforms. The novelty of this module is its involvement in the normalization protocol of benchmarking, integrating computational performance metric and physical fidelity. This process eventually bridges the quantitative and qualitative evaluations.

E. Comparative Matrix Construction

The agenda of this module is towards synthetizing the data that has been extracted and benchmarked into a comparison matrix. It initiates by tabulating the result sourcing from different UAV platforms under different evaluation metrics. The weighted scores are applied depending upon relevance of the research. For example , maximized weights are assigned for AI/ML model integration followed by analyzing the outcomes. The novelty of this module is that it establishes the weighted comparative matrix techniques that is capable of contextualizing the suitability of UAV platforms towards particular requirements in research work. This module also assists in offering clear information associated with the strength and weakness of varied UAV platforms on various metrics of assessment; thereby, deeper insight towards comparison is facilitated.

F. Analytical Synthesis

This module of operation derives the interpretative insights associated with domain alignment, trade-offs, and suitability of UAV platforms. The outcomes of the comparative matrix are analyzed in order to determine both deficiencies and dominant features (viz. computational cost vs realism). Further, thematic insight is generated towards each class of UAV platforms. The novelty of this module is that it employs correlation analysis of both feature and performance generating actionable guidance towards researchers for opting designs of UAV scenarios.

G. Gap Identification

This is the last module in architecture that is meant to determine the methodological and technological gap residing in present-state of UAV simulation tools. The identified limitations originated while benchmarking is mapped (e.g. lack of cloud scalability, restricted support of swarms, etc.). All the identified gaps are categorized into methodological (e.g. absence of standard benchmarks) and technical (e.g. physics realism). Finally, a roadmap towards next-generation designs of UAV scenarios is briefed focusing on realism, interoperability, and adaptability. The module facilitates forward-looking synthesis, integrating priorities of industrial development with empirical outcomes of research.

Accomplished Result

The implementation is carried out on a varied workstation with NVIDIA RTX 4090 GPU with 24 GB VRAM. The involvements of various software are OpenUAV, which is docker-based cloud instance with JMAVSim with PX4-v1.14-SITL, FlightGear 2020.3, AirSIm-v1.9(Unreal Engine 5), Gazebo 11 with ROS Noetic, and MATLAB R2024a. Standardized control parameters and quadrotor dynamics were used for configuring each platform for retaining consistency on multiple UAV platforms. The study consists of 10 independent runs of simulation being carried out for every UAV simulator for each type of mission (viz. swarm coordination, obstacle avoidance, waypoint navigation, etc.) that involves a total of 180 seconds of simulation time for each run. Custom telemetry scripts using MATLAB and python were used for logging the results accomplished for extracting data based on environment stability, control error, sensor latency, utilization of CPU/GPU, and frame rate. Averaging of quantitative metrics were carried out over all runs followed by normalizing scores of 0-1 towards assessing comparability. The outcomes are shown in Table 1-3 acquired from a rigorous configuration to show that numerical scores are unbiased and reproducible comparison towards design platforms of heterogeneous UAV scenarios. The implementation is carried out using standardized UAV mission dataset [26].

The outcome of Table 1 shows that X-Plane has accomplished the increased stability of 0.97 and minimal control error of 0.26m. This outcome showcases highly enhanced aerodynamic fidelity. The result also shows that AirSim offers the optimal visual realism that is seen to be characterized with minimal latency which is highly appropriate for AI/ML research. Higher computational efficiency has been exhibited by JMAVSim with 57% of minimal CPU usage; however, they have increased controlled error of 0.41m. The outcome of Table 2 has following key observations that OpenUAV and AirSim is found with superior and enriched features with average score > 8.4 highlighting its better performance. The overall best performance is exhibited by Gazebo when swarm supports are integrated with ROS extensibility and physics.The strongest HIL integration with score of 10 with balanced profile is maintained by MATLAB UAV toolbox. The outcome in Table 3 showcases the similar trend where highest ERI (0.84) is exhibited by X-Plane platform thereby computational efficiency is found balanced with high physics realism. The next better performance is shown by AirSim (with a score near to 0.80) accomplishing potential visual fidelity with increased computational cost.

Table 1. Core Simulation Performance Metrics (Average of 10 Trials)

Platform	Avg FPS	CPU Utilization (%)	Sensor Latency (ms)	Control Error (m)	Simulation Stability (0–1)
MATLAB UAV Toolbox	52	68	45	0.31	0.93
Gazebo	47	71	52	0.35	0.90
AirSim	58	76	40	0.28	0.95
X-Plane	62	64	38	0.26	0.97
FlightGear	49	70	55	0.33	0.89
JMAVSim/PX4 SITL	66	57	60	0.41	0.88
OpenUAV	54	65	49	0.34	0.91

Table 2. Feature Coverage Score (0–10 scale per category)

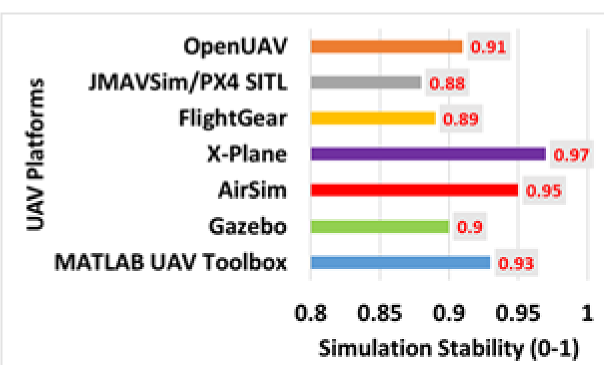
Platform	Scenario Flexibility	Physics Fidelity	Sensor Modeling	Swarm Simulation	HIL Support	AI/ML Integration	Realism	Extensibility (APIs/ROS)	Avg. Feature Score
MATLAB UAV Toolbox	9	7	9	5	10	6	7	9	7.8
Gazebo	9	8	9	9	7	7	7	10	8.3
AirSim	10	9	10	6	5	10	10	8	8.5
X-Plane	7	10	8	5	8	4	9	7	7.2
FlightGear	7	8	7	5	9	4	7	8	6.9
JMAVSim / PX4 SITL	6	7	6	4	9	4	6	9	6.4
OpenUAV	9	8	9	9	7	7	8	10	8.4

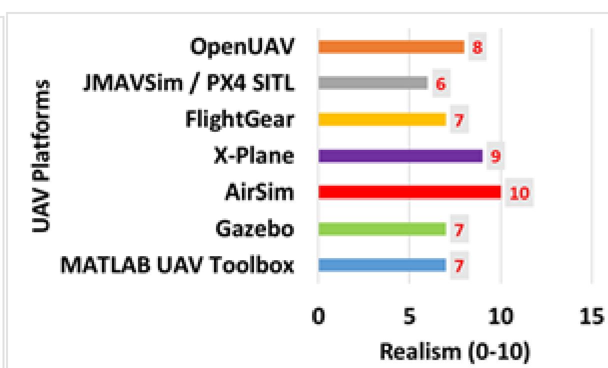
Table 3. Normalized Efficiency–Realism Index (ERI)

Platform	Computational Efficiency (0–1)	Environment Realism (0–1)	ERI = (0.5×Efficiency + 0.5×Realism)
MATLAB UAV Toolbox	0.72	0.75	0.74
Gazebo	0.70	0.70	0.70
AirSim	0.65	0.95	0.80
X-Plane	0.78	0.90	0.84
FlightGear	0.72	0.73	0.73
JMAVSim/PX4 SITL	0.90	0.55	0.72
OpenUAV	0.75	0.80	0.78

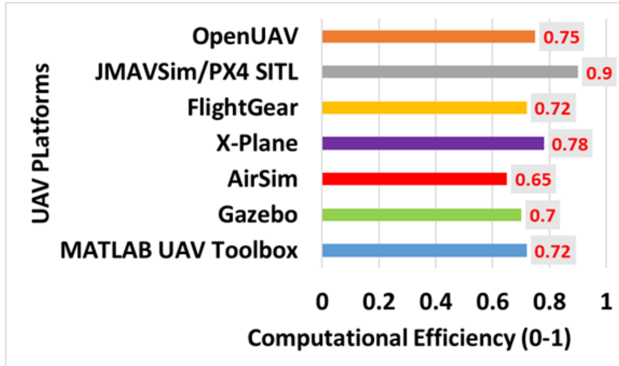
In a nutshell, AirSim exhibited 12% enhancement in cumulative simulation realism in contrast to Gazebo while there is 17% reported improvement exhibited by X-Plane in aerodynamic stability in contrast to FlightGear. OpenUAV exhibited around 10% maximization in swarm scalability in contrast to Gazebo exhibiting its cloud-native efficiency. The learning outcomes of the study are as follows:

1. The accomplished study outcome confirms UAV simulation tools are proven to specialize towards physics, swarm, and control. This ensures the demands of a context-centric platform of selection in research work. It will eventually mean that none of the standalone UAV platforms are actually universally optimal.
2. Both AirSim and X-Plane are noted to show potential realism; however, they demand extensively increased system resources. On the contrary, gazebo and JMAVSim are found to optimize efficiency at the cost of detailed physics. This represents a notable trade-off between physics fidelity and computational efficiency.
3. In perspective of hardware-in-the-loop testing, the performance of MATLAB UAV Toolbox is noted to be superior. It also shows tight integration with the Simulink model that is essential for control research towards embedded UAV environments.
4. The experimentation based on team and multi UAV is enabled by the distributed framework of OpenUAV. Its capability is maximized reportedly towards any cooperative mission-based study. This showcases higher scope of swarm simulators and collaborative research in future too.
5. The study outcome also finds that both python-based API and visual realism are quite superior for tool AirSim. This makes it quite a suitable environment for reinforcement learning, computer vision, and machine learning.





(a) (b)



(c)

Figure 2. Accomplished Study Outcomes

The dominant study outcomes are exhibited in Fig.2 to exhibit that simplified metrics towards judging the final score of effectiveness are simulation stability (Fig.2(a)), realism (Fig.2(b)), and computational efficiency (Fig.2(c)). The other metrics shown in Table 1, 2, and 3 are equally important too. The numerical outcome showcases research-oriented applicability towards scenario design of an UAV. The outcome of numerical findings exhibits increased supportability towards the objective of study by aligning itself with each quantitative strength of UAV simulation tool in terms of its role in practical research. The final outcomes of the comparative study are as follows: i) MATLAB UAV Toolbox offers optimal performance for control system research, ii) OpenUAV and Gazebo are highly suitable for research areas in robotics and swarm, iii) AirSim is found highly suitable for adoption in research work in computation vision and AI/ML based modelling, iv) FlightGear and X-Plane is noted to be highly suitable for Aerodynamic analysis, and v) JMAVSim is highly suitable for rapid testing.

The comparative study outcome shows the significance of the hybrid UAV simulation ecosystem. It is essential that design platforms complying with future scenarios should merge with cloud scalability of OpenUAV, the AI capabilities of AirSim, and realism of X-Plane. It is strongly anticipated that establishing cross-platform interoperability layers and standard benchmark will potentially improvise the reproducibility and boost the simulation research in UAV.

Conclusion

This paper presents a highly comprehensive comparative analysis towards UAV simulation platforms exhibiting its research applicability, limitation, and capabilities. Different from existing review and survey work, this paper performs extensive experiments to excavate the empirical outcomes of top-notched UAV platforms e.g. OpenUAV, JMAVSim, FlightGear, X-Plane, AirSim, Gazebo, and MATLAB UAV Toolbox. The outcome shows that almost all of them have got potential as well as shortcomings. The proposed study contributes to innovativeness by facilitating an integrated computational framework towards assessing UAV platforms followed by identifying strength and weakness.

The future work will be carried out towards extending the current framework towards cooperative delivery missions of multi-UAV scenarios. The idea will be to integrate trajectory optimization using AI with blockchain and real-time sensor fusion. The motive will be towards improving operational reliability and scalability in UAV operations while designing a novel simulation platform.

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