A Hybrid Learning Framework for Energy-Aware and Safe UAV Package Delivery

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Abstract: In the area of transportation and logistics, Unmanned Aerial Vehicle (UAV) offers certain unique advantage towards package delivery services in terms of environmental impact, operational cost, and delivery time. Review of literatures shows active participation of Artificial Intelligence (AI) is noted to be predominantly assumed as effective solution. Therefore, the proposed study introduces a hybrid approach for safer, autonomous, and cost-effective dispatching of the package from one to another location. The hybrid model uses reinforcement learning for path planning in adaptive manner while supervised learning is used for optimizing energy with payload awareness. Implemented in python, the proposed hybrid model is tested on standard dataset to find it offers 98% of mission success rate with consumption of only 5.9 minutes with minimal energy consumption in contrast to baseline methods.

Keywords: Simulation Unmanned Aerial Vehicle, Navigation, Package delivery, Energy, path planning, Artificial Intelligence

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Introduction

Package delivery system using Unmanned Aerial Vehicle (UAV) make use of drones either autonomously or semi-autonomously for moving the goods or an object from one to another location [1]. Although, such system is very novel and cannot be notably seen to be used commercially, but they have been initiated already in smaller scale commercial system. UAV-based delivery system offers on-demand delivery solution with higher cost-effectiveness while they are highly accessible during disaster or emergency situation [2]. Irrespective of such potential, the delivery system in UAV encounters various challenges which involves sensitivity to unpredictable weather condition, limitation of flight range, payload constraint, restricted better capacity. Apart from this, there are various issues associated with avoiding obstacle within sophisticated urban environment, security concerns, reliability of communication, collision risk, compliance of airspace regulation, etc. All these potentially affect the reliability and scalability of logistics in UAV [3]. One emerging way to solve this problem is via Artificial Intelligence (AI) based models either in form of Machine Learning (ML) model or Deep Learning (DL) model [4]. However, there are various challenges related to practical implementation of such algorithms. The primary challenge is related to sub-optimal quality and scarcity of data towards efficient model training as aggregating and annotating such data is not only expensive but highly risky too. The aim of the proposed study model is towards developing a novel hybrid machine learning model which is capable of facilitating UAV delivery system with higher safety, autonomous planning on dynamic environment, and is highly energy-efficient.

Proposed Method

The proposed study introduces a novel hybrid ML approach towards developing an innovative architecture for package delivery system in UAV. The complete work implementation is decomposed into two stages viz. i) stage-1 consists of planning of global path and avoiding obstacle while ii) stage-2 consists of management of energy consumption along with optimization of payload-aware trajectories. For this purpose, RL is used in stage-1 implementation while stage-2 implementation is carried out using Regression network.

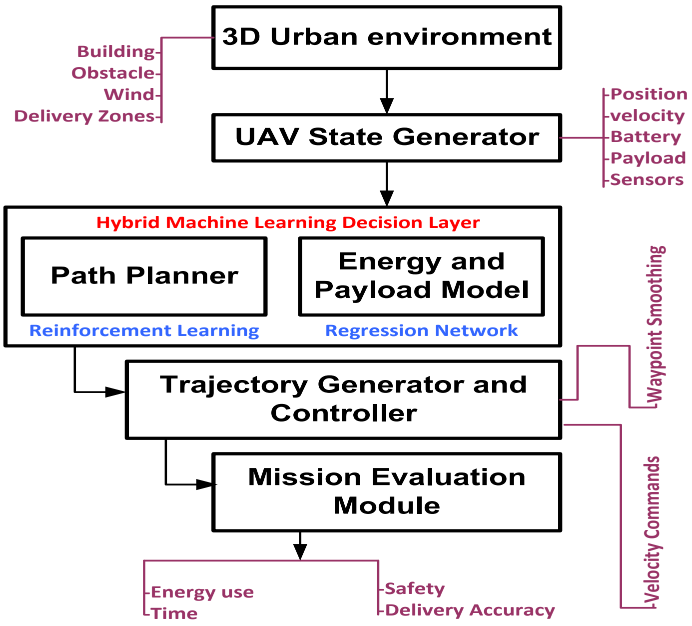


Figure 1. Architecture of Hybrid Model

Figure 1 highlights the adopted system architecture where it can be noted that proposed hybrid mechanism targets towards enhancing mission feasibility, trajectory efficiency, and convergence speed. The illustration of the essential functional blocks involved in proposed architecture towards accomplishing the study objective are as follows:

Mathematical Model

The proposed system models navigation problem of UAV in form of Markov Decision Process that can be empirically expressed as,

$$M=[\beta] \tag{1}$$

In the above equation (1), it can be noted that Markov process M is dependent on β which is further an array consisting of discount factor γ, reward function R, probability of state transition P, action space A, and state space S. The energy consumption associated with the proposed model is estimated using supervised model as follows,

$$Ener_t=\delta(x_t) \tag{2}$$

In the above equation (2), the computation of energy consumption is noted to be dependent upon neural network regressor δ with specific model parameters and input feature vector x_t. The system further computes Mean Squared Error (MSE) that is further minimized by training objectives in form of loss function as,

$$L(m_{param})=\frac{1}{N}\sum_{i=1}^{N}\Delta Ener^2 \quad (3)$$

In the above equation (3), ΔEner represents the difference between initial energy and current state of energy. Hence, the model contributes to distinguishing energy prediction from decision making for navigation followed by using the learned insight of an energy to the cumulative system. Hence, the model offers energy-aware and informed planning of flight path and complete mission. Further, polynomial is used for defining continuous trajectory as exhibited in equation (4),

$$l(t)=\sum_{i=0}^{n}\rho \quad (4)$$

In the above equation (7), l(t) represents the polynomial that is dependent upon a variable ρ which is product of coefficient ci and instantaneous time ti. Minimization is applied by the model to obtains ci coefficient as follows,

$$J=\int_0^T abs\left(\frac{a}{b}\right)^2 dt \quad (5)$$

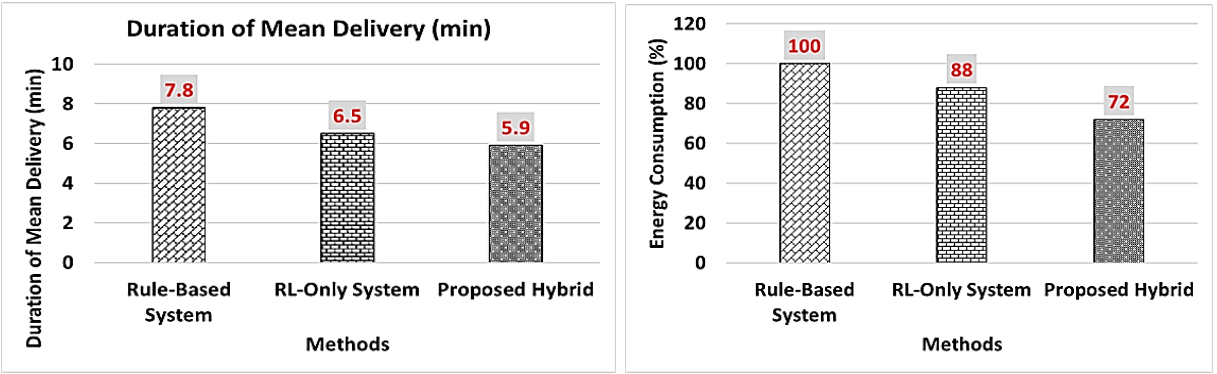
In the above equation (8), the numerator a represents $d^2l(t)$ and denominator b represent dt^2. This block address the issues related with unrealistic movement of UAV emerging from existing static navigation system.

Result Analysis

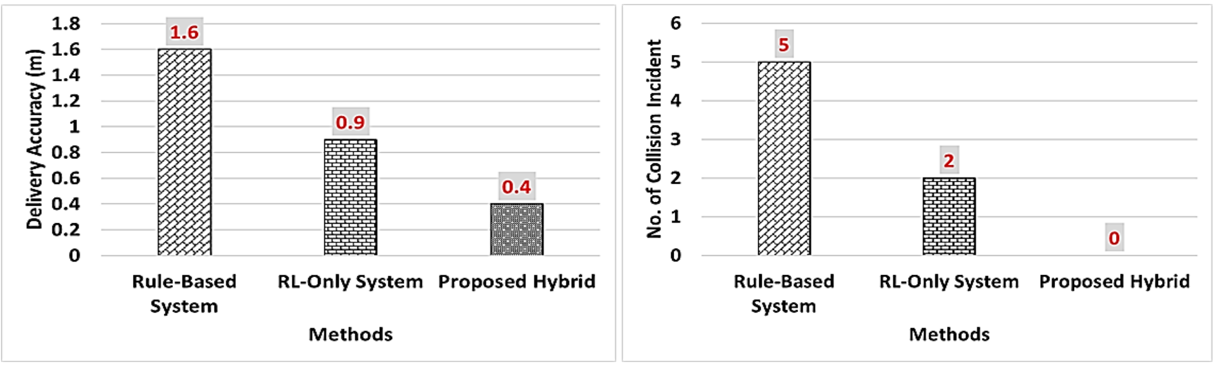
Python is used for simulating the proposed model along with adoption of OpenAI-Gym for forming environment towards UAV navigation. The experiment is carried out considering a dataset that consists of simulated flight records of UAV carried out in urban environment [5]. The outcome of the simulation study is accomplished by comparing the proposed system with two conventional baseline methods i.e., rule-based system and standalone RL.

Proposed hybrid model accomplished significantly higher success rates of mission by 98% in contrast to baseline models ranging between 85-92%. Apart from this, the fluctuation of delivery accuracy is only 0.4 which is notably lower than baselines. The number of collision incidents are almost none while existing baseline still encounters 2-5 collisions. Further, energy of proposed hybrid is reduced to 16% and 28% in contrast to standalone RL model and rule-centric models. Interestingly, the duration of mean delivery for proposed system is 5.9 min whereas existing baseline ranges between 6.5-7.8min.

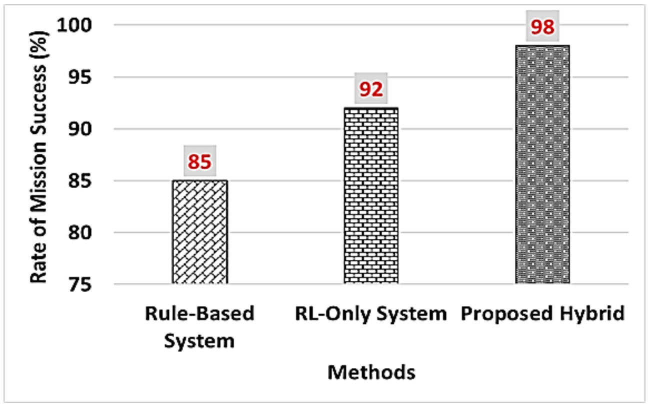
A lower delivery time is accomplished in proposed hybrid (Fig.2(a)) which is mainly due to inclusion of feedback system with energy awareness associated with supervised model. This control UAV to prevent a form of unwanted changes in altitude and detours which evidently cannot be carried out by either of the baselines. The inclusion of supervised learning is also the reason towards reduced energy consumption (Fig.2(b)). The prime reason behind this is UAV model chooses more efficient and safer path under different conditions of flights due to inclusion of supervised learning model in proposed hybrid. On the contrary, there is no inclusion of energy modeling in either of the baseline models while this reason leads to significant drain in battery life. This outcome also infers that if navigation learning is separated from energy estimation with dedicated AI module to control them, then it is actually feasible to enhance the sustainability of the cumulative mission towards package delivery system by UAV. The proposed system also exhibits higher delivery accuracy (Fig.2(c)) which is mainly due to highly controlled trajectories that are much smoother in both phases of delivering the package and final descent. It is also noted that proposed hybrid offers highly stable flight when it is near the delivery point while this is never attempted to be accomplished by current baseline models or any other methods in current literatures in UAV delivery system.



(a) delivery time *(b) Energy Consumption*



(c) Delivery Accuracy *(d) Collision Avoidance with Safety*



(e) Mission Success Rate

Figure 2. Benchmarked Study Outcome

One of the enriched learning outcomes of as a part of this result to ensure high accuracy of the delivery system of the UAV, it is essential to refine trajectories as well as have an intelligent navigation system. Further, it is noted that there is zero collision incident associated with the proposed study (Fig.2(d)). This is because of involved continuous learning strategy being incorporated within the proposed system towards the environment as well as towards formulating decision for obstacle avoidance. It is observed that there is no adaptability by rule-based baselines while standalone RL model is more inclined on giving importance of accomplishing goal (accuracy) rather than any focus on safety. This problem is addressed by proposed hybrid system which offers balance between efficiency as well as safety. Hence, the proposed study model focuses both on auxiliary learning inputs as well as significance of highly structured reward design system. Finally, proposed hybrid system is noted to offer higher rate of mission success (Fig.2(e)) which is mainly due to joint optimization of trajectory smoothness, energy usage, and navigation.

Conclusion

The proposed study presents a hybrid ML-centric package delivery system using UAV. This paper discussed the mathematical modelling aspect of the hybrid in order to justify the equal contribution being made by all the involved operational modules. The learning outcomes of the model are i) both efficiency and safety are simultaneously enhanced by hybrid learning system, ii) practical delivery success in UAV demands decision making with energy awareness, and iii) both performance and system stability can be significantly enhanced by distinguishing the learning task. The future work will be carried out towards further optimization of current work towards addressing unforeseen emergency situation.

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