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EVENT-TRIGGERED ADAPTIVE CONTROL AND ENERGY-EFFICIENT TRAJECTORY PLANNING FOR CARGO DRONES USING GIS AND SPIKING NEURAL NETWORKS

Research paper

Sergiu Popa[1*], Flavius-Maxim Petcuț[2], Anca-Adriana Petcuț-Lasc[3], Valentina-Emilia Balaș[4]

[1,3]Petroleum-Gas University of Ploiești, Doctoral School, Ploiești, Romania
[2,3,4]"Aurel Vlaicu" University of Arad, Faculty of Engineering, Arad, Romania
[4]Academy of Romanian Scientists, Bucharest, Romania

Abstract: Cargo transport with unmanned aerial vehicles (UAVs) is constrained above all by the energy stored on board, so every joule spent on propulsion, computation or communication reduces the payload and the range of the mission. This paper reviews thirteen works published between 2017 and 2025 along four directions that address this constraint: event-triggered control, trajectory planning based on geographic information systems (GIS), energy-efficient trajectory optimization, and spiking neural networks (SNNs) used as controllers. The review shows that these directions are usually treated in isolation, although they act on complementary parts of the energy budget. On this basis the paper proposes a three-layer control architecture in which a GIS layer produces an energy-aware reference trajectory, a monitoring layer evaluates a triggering condition on the state of the UAV, and an adaptive layer keeps a conventional proportional-integral-derivative (PID) controller in nominal operation and activates an SNN only when an event is detected. The architecture is presented at conceptual level; its implementation in MATLAB/Simulink and its validation on the Quanser platform of the "Aurel Vlaicu" University of Arad are the subject of further work.
Key words: *unmanned aerial vehicles, event-triggered control, spiking neural networks, GIS, energy efficiency*

INTRODUCTION

Unmanned aerial vehicles are moving from observation tasks towards the transport of goods. Cargo drones are considered today for last-mile delivery in congested cities, for medical logistics and for supplying locations that are difficult to reach by road. Compared with a van, an electric multirotor avoids road congestion and produces no local emissions during flight, which makes it attractive from the point of view of environmental protection as well. The decisive limitation, however, is not the payload the airframe can lift but the energy stored in its battery.

This limitation is more restrictive than it appears, because the energy available on board is consumed by three different processes. Propulsion consumes most of it, and it depends directly on the geometry of the flight path, on speed and on acceleration. Computation and communication consume a smaller but non-negligible share, and their contribution grows when the control law is evaluated and transmitted at a high fixed rate. Finally, part of the energy is wasted in corrections that the aircraft performs when it meets wind gusts, sensor noise or deviations that were not anticipated during planning. A solution that reduces the consumption of one of these processes while increasing that of another brings no real gain over the mission. Each of these processes has been treated in literature, but largely separately. Energy-aware trajectory planning is addressed in work on coverage path planning and on communication-oriented trajectory optimization. The cost of computation and communication is addressed in work on event-triggered control, where the control law is updated only when the tracking error leaves an admissible region. The cost of unanticipated corrections is addressed in work on adaptive and intelligent control, and more recently by spiking neural networks running on neuromorphic hardware. Geographic information systems appear in a fourth group of works, as a source of the geospatial data needed for realistic planning in urban environments.

[1]Corresponding author, sergiupopa20@yahoo.com, 0009-0006-1417-4601
[2]flavius.petcut@uav.ro, 0009-0001-6928-4019
[3]anca.petcut@uav.ro, 0009-0000-5450-5272
[4]balas@drbalas.ro, 0000-0003-0885-1283

The present paper has two objectives. The first is to review these four directions in a comparable form, with emphasis on the mechanism through which each of them saves energy and on the limitations reported by the authors. The second is to derive from this review a control architecture for cargo drones that combines them in a single structure, in which artificial intelligence is used only when the flight conditions require it rather than permanently. The main contribution of this work is the conceptual integration of GIS-based energy-aware trajectory planning, event-triggered monitoring and SNN-assisted PID adaptation within a unified architecture for cargo UAVs. The paper is the starting point of doctoral research and therefore proposes the architecture at conceptual level, without experimental validation.

MATERIAL AND METHODS

The review was carried out on thirteen works published between 2017 and 2025, selected to cover four directions relevant to the energy budget of a cargo UAV. Journal articles were taken from IEEE Transactions, from the Arabian Journal for Science and Engineering and from the journal Drones, and conference papers from four IEEE conferences (ICRA, ICTC, EIT and HPSR) and from Robotics: Science and Systems. Each work was analyzed with respect to the same three questions: which part of the energy budget it addresses, by which mechanism, and what limitations its authors report. The general state of the art on artificial intelligence applied to drone control, surveyed by Caballero-Martin et al. (2024), was used as the reference framework for this classification.

Event-triggered control of unmanned aerial vehicles

In classical digital control the control law is evaluated at fixed time instants, regardless of whether the state of the aircraft has changed. Event-triggered control replaces this fixed rhythm with a condition: the control law is recomputed only when the deviation of the current state from the state at the last update exceeds a threshold. Tian et al. (2021) apply this principle to the attitude control of a quadrotor through an event-triggered super twisting algorithm and prove, by a Lyapunov analysis, that the triggering sequence is free of Zeno behavior, that is, that the events cannot accumulate infinitely in a finite interval. Shao et al. (2021) combines the triggering mechanism with a discrete-time neural controller and a disturbance observer, treating at the same time the saturation of the inputs. Wu et al. (2024) extend the approach to the cooperative control of a group of six-rotor UAVs with prescribed finite-time performance, with the explicit aim of saving transmission resources. Cuenca et al. (2019) study the same problem from the perspective of the communication network and show, on a UAV test-bed, that periodic event-triggered sampling combined with dual-rate control reduces network utilization considerably while keeping control performance satisfactory.
The common result of these works is that a large part of the control updates performed at a fixed rate carry no useful information. The common limitation is that the triggering threshold governs a trade-off: a high threshold saves computation and transmissions but degrades tracking, and a low threshold brings the behavior back towards periodic control.

Trajectory planning based on geographic information systems

A trajectory computed in free space is of little use over a city. Rokhsaritalemi et al. (2018) plan drone trajectories for three-dimensional urban modelling starting from GIS layers, considering the visibility of the facades to be scanned and the obstacles present. Sulaiman et al. (2020) use GIS data and building models to generate automatically the flight plan of camera-equipped UAVs for fire emergency response, where the plan must be produced quickly and must avoid risk areas. In both cases the geospatial database supplies information that the aircraft cannot obtain by itself during flight: the height of buildings, the position of vegetation, restricted areas, and the shape of the terrain. The limitation reported is the dependence on the quality and the age of the geospatial data, which in a real urban environment are not always up to date.

Energy-efficient trajectory optimization

Zeng and Zhang (2017) derive a theoretical model of the propulsion energy of a fixed-wing UAV as a function of speed, direction and acceleration, and use it to optimize the trajectory jointly with the communication throughput, defining energy efficiency as the number of bits transmitted per joule consumed. The model makes explicit the fact that accelerations and changes of direction, not distance alone, dominate consumption. Shivgan and Dong (2020) exploit the same observation in coverage path planning: they formulate the problem as a travelling salesman problem, solve it with a genetic algorithm and reduce in particular the number of turns, reporting a consumption between two and five times lower than that of a greedy algorithm. Ahmed et al. (2024) extend the problem to a fleet of UAVs covering several regions, adding the management of recharging. The limitation of this direction is that the optimization is performed offline, on an assumed model of the environment; wind and the real behavior of the battery are not known at planning time.

Spiking neural networks used as controllers

Spiking neural networks process information through asynchronous impulses rather than through values updated at a fixed rate, which makes them naturally compatible with an event-driven mode of operation. Stagsted et al. (2020) implement a complete PID controller as a spiking network on a neuromorphic chip and show that the structure of the classical controller can be reproduced with spiking neurons at very low power consumption. Vitale et al. (2021) combines event-based vision with neuromorphic processing for the control of a UAV, obtaining low latency in the reaction to disturbances. Yu et al. (2025) use an SNN for fault-tolerant attitude tracking, keeping the stability of the aircraft when actuators fail. The limitations reported concern the training of such networks, which is more difficult than for conventional networks, and the availability of neuromorphic hardware qualified for flight. Table 1 summarizes the four directions.

Table 1. Summary of the reviewed research directions

Research direction	Main contribution	Reported benefit	Key references
Event-triggered control	The control law is updated only when a triggering condition on the tracking error is violated.	Fewer control updates and network transmissions at comparable tracking performance.	Tian et al. (2021); Shao et al. (2021); Wu et al. (2024); Cuenca et al. (2019)
GIS-based trajectory planning	Flight paths are generated from geospatial layers: buildings, vegetation, visibility and restricted areas.	Shorter and safer routes; automatic mission planning in dense urban areas.	Rokhsaritalemi et al. (2018); Sulaiman et al. (2020)
Energy-efficient trajectory optimization	Path and speed are optimized against an explicit propulsion-energy model.	Reported energy savings from a factor of two up to five compared with greedy planning.	Zeng & Zhang (2017); Shivgan & Dong (2020); Ahmed et al. (2024)
Spiking neural networks for control	Control and adaptation are computed with asynchronous spiking neurons on neuromorphic hardware.	Low latency and low power consumption; tolerance to sensor noise and actuator faults.	Stagsted et al. (2020); Vitale et al. (2021); Yu et al. (2025)

RESULTS AND DISCUSSION

The review shows that the four directions act on different and complementary parts of the energy budget: GIS planning and energy-aware optimization act before the flight, on the reference trajectory; event-triggered control acts during the flight, on the cost of computation and communication; spiking networks act on the quality of the reaction to disturbances and on the power consumed by the adaptation itself. None of the works reviewed combine all four. The architecture proposed below is built on this observation and is shown in Fig. 1.

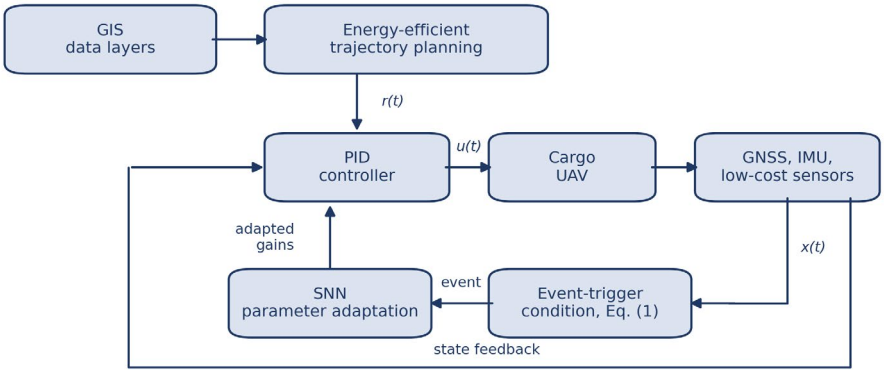


***Fig. 1**. Proposed three-layer control architecture for a cargo UAV*

Planning layer

The planning layer builds the reference trajectory *r*(*t*) from GIS layers, following Rokhsaritalemi et al. (2018) and Sulaiman et al. (2020): buildings and their heights, vegetation, restricted and risk areas, and the wind field estimated for the corridor of the mission. The route is not chosen for minimum length but for minimum energy, according to the propulsion model of Zeng and Zhang (2017), which penalizes accelerations and changes of direction. The total energy of a mission is written as

$$E_{total} = \int_0^T P_{prop}(v, a, w)\, dt + N \cdot E_{upd} \tag{1}$$

where P_{prop} is the propulsion power as a function of speed v, acceleration a and wind w, N is the number of control updates performed during the mission and E_{upd} is the energy consumed by one update, including the associated transmission. The first term is reduced by planning, the second by the mechanism described below.

Monitoring layer

During the flight, the state of the aircraft is estimated by GNSS, by the inertial measurement unit and by low-cost sensors. Following Tian et al. (2021) and Shao et al. (2021), an event is declared when the deviation between the current state and the state recorded at the last update t_k exceeds a relative threshold,

$$\|x(t) - x(t_k)\| \geq \sigma \|x(t)\| + \varepsilon \tag{2}$$

where σ is the relative threshold and ε is a strictly positive constant. The role of ε is not only numerical: as shown by Tian et al. (2021), a strictly positive term guarantees a minimum interval between two consecutive events and therefore excludes Zeno behavior. Between two consecutive events the control law is held at the value computed at t_k, so that the number of

updates follows the actual behavior of the aircraft rather than a fixed clock: a quiet flight segment produces few updates, while a wind gust produces several in quick succession.

The relative reduction in the number of control updates, with N_{ET} the number of event-triggered updates and N_P the number of periodic updates over the same interval, can be expressed as

$$\eta = 1 - N_{ET} / N_P \quad (3)$$

Adaptive control layer

In nominal conditions the aircraft is controlled by a conventional PID controller, whose parameters are those determined at commissioning. This choice is deliberate: a PID controller is predictable, inexpensive in computation and accepted in certification procedures. The SNN receives the tracking error and selected UAV state variables and provides bounded corrections to the PID gains. The SNN is therefore used as an adaptation mechanism and not as the primary controller, which keeps the behavior of the system predictable between events. Recent experimental results have also shown that intelligent adaptation of conventional PID control, such as fuzzy-PID control, can improve UAV flight stability compared with traditional PID control (Wu et al., 2025). The choice of a spiking network for this role follows from the works of Stagsted et al. (2020), Vitale et al. (2021) and Yu et al. (2025): such a network is inexpensive in energy, reacts with low latency and tolerates noisy measurements, which are exactly the properties required for an adaptation that is activated rarely and must respond quickly.
Compared with the solutions reviewed, the expected benefit of the architecture is that the three savings are cumulative rather than alternative: the trajectory is energy-aware before take-off, the control law is evaluated only when necessary, during flight, and the adaptation itself is performed on a low-power substrate. The architecture also keeps the computational load low in nominal flight, which matters for a cargo drone whose on-board computer is dimensioned for the worst case.
Several questions remain open and are assumed as such. The choice of the pair (σ, ε) is a compromise between energy saving and tracking accuracy, and it is not obvious that a single pair is suitable for the whole mission; a threshold that adapts to the flight phase is a possible development. The training of the spiking network requires representative data on disturbances, which for a cargo drone are difficult to obtain other than experimentally. Finally, the GIS layer introduces a dependence on the quality of the geospatial data, and an outdated database can produce a trajectory that is energy-optimal but unsafe. These questions can only be answered by implementation and experiment.

CONCLUSION

The energy available on board a cargo drone is consumed by propulsion, by computation and communication, and by the corrections performed in the face of unanticipated disturbances. The literature reviewed in this paper treats these three sources separately: GIS-based planning and energy-aware trajectory optimization reduce the first, event-triggered control reduces the second, and spiking neural networks act efficiently on the third. The works reviewed show that each mechanism is effective on its own, and also that each has a clear limitation when used alone.
The paper proposed a three-layer architecture that combines them: a GIS planning layer that produces an energy-aware reference trajectory, a monitoring layer that evaluates a triggering condition with a guaranteed minimum inter-event interval, and an adaptive layer in which a PID controller operates nominally and a spiking neural network intervenes only at events. The essential idea is that artificial intelligence is used when the situation requires it and not permanently, which is expected to reduce the energy consumption and the computational load in nominal flight.

The architecture is proposed here at conceptual level. The next stage of the work is its implementation in MATLAB/Simulink, for which the "Aurel Vlaicu" University of Arad holds a Campus license, followed by experimental validation on the Quanser platform available in the university laboratory. The quantities of interest for this validation are the reduction ratio defined in equation (3), the total mission energy given by equation (1) and the tracking error, measured comparatively against a conventional periodic PID controller.

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