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A Holistic Framework for Assessing and Optimizing Energy Consumption for Low-Altitude Air City Transport Systems

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Abstract— **Traffic air congestion should be considered in future deployments of Low-Altitude Air city Transport (LAAT) systems. In addition to the congestion concerns, the low-altitude aircraft is being designed with limited energy capacity due to design constraints and battery technologies, e.g., electric vertical takeoff and landing vehicles (VTOLs). Hence, energy consumption concerns should also be considered within LAAT operations. This paper examines the energy consumption of low-altitude aircraft in air mobility (AM) operations, intending to improve the environmental impact of air mobility in urban and regional areas. To achieve this, the study enhances the LAAT model-based operational framework by integrating an energy consumption model (ECM) for low-altitude aircraft. The framework couples modeling and control of microscopic and macroscopic levels of AM operations. Including the ECM allows us to explore the relationship between macroscopic energy consumption and known macroscopic traffic flow variables. As a result, this paper contributes to the literature with the development of the LAAT Energy Consumption Model (LeM). The LeM does not only quantify the energy consumption of individual aircraft but also facilitates the aggregation of energy consumption for the entire airspace. The study realizes LeM with a simplified feedback control design, i.e., a gating policy, which optimizes the number of aircraft allowed into the network, balancing energy efficiency and traffic efficiency in LAAT networks. The development of the LeM provides a valuable tool for assessing the environmental impact of LAAT systems. LeM can be a benchmark to diagnose airspace conditions and enhance traffic control strategies for operating efficiently and sustainably of LAAT systems.**

I. INTRODUCTION

The aviation ecosystem is continually advancing with the development of cutting-edge technologies. New aircraft designs are being created to enhance air mobility (AM)[1]. These innovations aim to revolutionize commute possibilities and cargo transport within and between cities, operating in low-altitude airspace and forming what can be termed the low-altitude air city transport (LAAT) system.

The literature highlights the growing interest in deploying low-altitude aircraft in the airspace [1]. Most of these aircraft are electrically powered, utilizing advanced batteries, and capable of vertical take-off and landing. The success of such designs lies in their ability to be remotely or autonomously controlled, with or without a pilot. This integration of advanced technologies enhances AM operations, ensuring safety and efficiency and providing a platform for ground-breaking research in this frontier domain.

The rapid advancements in unmanned aerial vehicles (UAVs) and electric vertical takeoff and landing vehicles (VTOLs) have drawn significant attention to the critical issue of energy consumption in aerial transportation systems. As these autonomous aerial vehicles become increasingly prevalent, understanding and optimizing their energy usage have become paramount for sustainable and efficient operations. Early research by Thibbotuwawa et al. [2] shed light on the factors influencing energy consumption during UAV missions, paving the way for investigating the relationship between energy consumption and routing decisions. They provided a comprehensive overview of energy consumption's impact on UAV routing, categorizing the influencing parameters and establishing crucial relationships between them and energy usage.

Connectivity and digitalization will enable new control measures in aviation operations and open new ways for integrating these measures in real time urban traffic management. Hence, new control strategies can be designed to regulate LAAT demand and supply. This can be achieved by manipulating aircraft departures, aircraft routings, aircraft speed, etc. It should be noted that LAAT controlled systems might create system queues, which have a high impact on the system's efficiency and can lead to environmental and economical challenges. Hence, this study focuses on incorporating the energy aspects into the traffic control strategies, by (i) investigating an energy consumption model (ECM) of the low-altitude aircraft and aggregating the traffic characteristics in the network level, and (ii) designing a feedback control strategy with gating policy based on the energy consumption in the network, as depicted in Fig. 1. To the authors' knowledge, integrating *ECM* with *gating policy* for LAAT systems has never been investigated.

Traffic flow models are beneficial for developing strategies for LAAT systems. The Macroscopic Fundamental Diagram (MFD) proves to be a powerful tool for understanding and managing vehicular networks [3]. Utilizing an MFD-based model for the LAAT control problem offers advantages by simplifying complexity through information aggregation at the macroscopic level while transforming control actions to the microscopic level. By developing collective and aggregate aircraft traffic flow models for LAAT systems, feedback traffic control strategies can be designed. Similarly, studies in ground traffic have focused on the environmental aspect of large-scale traffic networks, examining carbon emissions in relation to additional traffic characteristics [4].

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[1]In this paper, we use the term *air mobility (AM)* to refer to the futuristic air mobility industry within urban and regional areas, encompassing both *urban air mobility (UAM)* and *advanced air mobility (AAM)*.

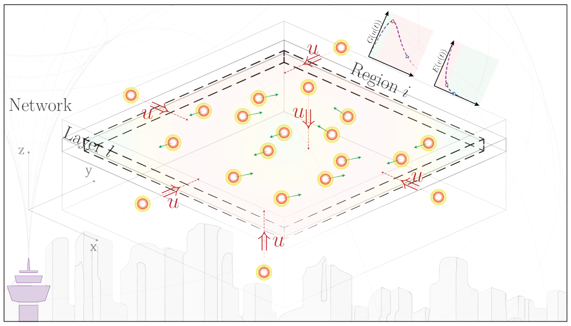

Fig. 1. A schematic digitalized LAAT network consists of layers ($l \in \mathcal{L}$) divided into regions ($i \in \mathcal{R}$), with gating control input u which balances the system's outflow $G(n)$ (as a function of accumulation n) and energy consumption $\mathrm{E}(V)$ (as a function of speed V).

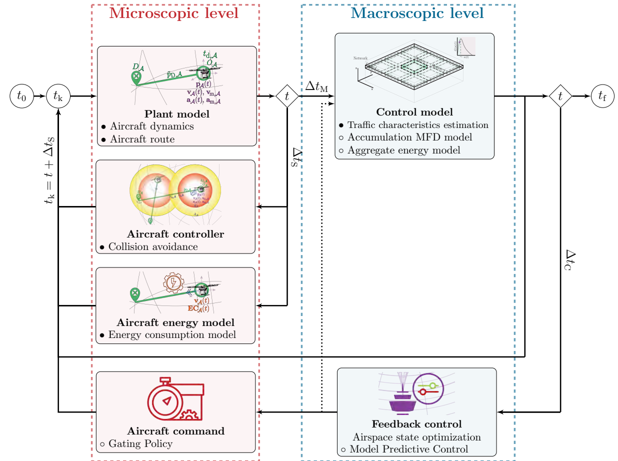

Fig. 2. LAAT model-based operational framework with aircraft energy consumption model, while combining the microscopic and macroscopic levels of LAAT controlled systems.

This paper explores the environmental aspects of AM operations by studying the energy consumption of low-altitude aircraft in the airspace. We extend the LAAT model-based framework [5] with an energy consumption model (ECM) [2]. This integration allows us to study the relationship between macroscopic energy consumption and known macroscopic traffic flow variables, leading to the derivation of the LAAT Energy Consumption Model (LeM). LeM is utilized to design a simplified feedback control strategy, i.e., a gating policy to optimize the number of aircraft allowed to enter the network. This policy balances the system's outflow and energy consumption, exploring trade-offs between energy efficiency and traffic efficiency in LAAT networks.

II. DEVELOPING LAAT ENERGY CONSUMPTION MODEL

A. LAAT model-based operational framework

The LAAT model-based operational framework, which was developed in [5], [6], is extended to include an energy consumption model (ECM) for the low-altitude aircraft, as shown in Fig. 2. The framework couples modeling and control of LAAT systems and integrates the two aggregation levels, i.e., microscopic and macroscopic. In this paper, ECM is applied in the framework to determine the energy consumption of each aircraft as part of the plant model. The aircraft energy consumption can be easily aggregated for the whole airspace, and by then to derive a macroscopic energy consumption model, namely LAAT energy consumption model (LeM). The uniqueness of this framework is that LeM can straightforwardly diagnose the airspace conditions and enhance traffic control strategies, to efficiently and sustainably operate LAAT systems.

The framework presented in this study uses a microscopic model as the plant model to describe aircraft behavior in detail, while a macroscopic model is used as a control model for designing control inputs. The aggregate dynamics of the macroscopic level are steered by the traffic LAAT dynamics of the microscopic level, with the characteristics variables being inserted as an input to the control model. Simultaneously, a feedback control strategy is created to optimize the airspace state operationally, following the airspace dynamics and identification. Finally, the optimal control inputs are calculated and transferred to the microscopic level through an aircraft command subsystem. This process is illustrated in Fig. 2.

Incorporating the Energy Consumption Model (ECM) into the LAAT model-based operational framework opens up new directions for investigating the energy consumption and traffic characteristics in LAAT networks. The extended framework allows us to identify the relationship between macroscopic energy consumption and known macroscopic traffic flow variables, and to derive the LAAT Energy consumption Model (LeM). As a result, it is possible to optimize the LAAT system's performance with respect to energy consumption characteristics. In this paper, LeM will be utilized with a simplified feedback control strategy to demonstrate the potential of macroscopic energy consumption models. The control strategy, a gating policy, will optimize the number of aircraft allowed to enter the network by maximizing system outflow and minimizing energy consumption, i.e., explore the trade-offs between energy efficiency and traffic efficiency in LAAT networks.

B. Energy consumption model for LAAT networks

In this paper, we follow the energy consumption model presented in [2] and adapt it to low-altitude aircraft, in order to estimate the total energy consumption in the LAAT network and to develop LeM. Note that the low-altitude aircraft is assumed to be a multicopter aircraft (without wings), where the aerodynamic factors are minor compared to fixed-wing or tilt-wing aircraft. Also, low-altitude aircraft are not expected to fly at relatively high speeds within or across cities, compared to aircraft flying in Class A–G.

According to the proposed model in [2], while the aircraft is flying, the energy needed to move in horizontal or vertical motion depends on different factors. The aircraft design parameters, such as weight, width, air density, drag coefficient, and surface area of the flying object, influence the aircraft energy consumption model. In recent studies, new models distinguish between vertical motion with or against gravity, see e.g. [7]. It should be stressed that more advanced models which fit different aircraft designs and types can be integrated into the framework without altering the methodology.

Given the LAAT model-based operational framework, it is possible to calculate the aircraft energy consumption according to the current aircraft speed. Assuming aircraft $\mathcal{A}$ is flying in a space $\mathbf{S}$, the aircraft velocity $\mathbf{v}_{\mathcal{A}} = [\mathbf{v}_{x,\mathcal{A}}, \mathbf{v}_{y,\mathcal{A}}, \mathbf{v}_{z,\mathcal{A}}] \in \mathbb{R}^3$ can be normalized for the horizontal direction to align with the model in [2] as follows

$$V_{xy,\mathcal{A}} = \mathrm{proj}_{xy}(\mathbf{v}_{\mathcal{A}})\,. \tag{1}$$

Then, the power used for horizontal flying $\mathrm{p}_{\mathrm{h},\mathcal{A}}$ [W] can be calculated as follows

$$\mathrm{p}_{\mathrm{h},\mathcal{A}} = \left(0.5 \cdot (C_D \cdot A \cdot D \cdot V_{xy,\mathcal{A}}{}^3) + \frac{W^2}{D \cdot V_{xy,\mathcal{A}} \cdot b^2}\right), \tag{2}$$

where C_D $[-]$ is the drag coefficient of the aircraft, A $[\mathrm{m}^2]$ is the front-facing area of the aircraft, D $[\mathrm{kg/m}^3]$ is the air density in the low-altitude airspace level, W [kg] is the total weight of the aircraft, and b [m] is the rotor radius of the aircraft.

Additionally, the power used for vertical flying $\mathrm{p}_{\mathrm{v},\mathcal{A}}$ [W] is constant relative to the motion, i.e., depending only on the travel time, and can be calculated as follows

$$\mathrm{p}_{\mathrm{v},\mathcal{A}} = \left(\frac{(W \cdot g)^{3/2}}{\sqrt{2 \cdot D \cdot A}}\right), \tag{3}$$

where g [N] is the gravity coefficient.

Finally, the energy consumption of aircraft $\mathcal{A}$ for the travel time $\tau_{\mathcal{A}}(t)$, i.e., $\mathrm{E}_{\mathcal{A}}(t)$ [Wh], according to the horizontal speed $V_{xy,\mathcal{A}}(t)$ at time t, is calculated as follows

$$\mathrm{E}_{\mathcal{A}}(t) = \int_{t-\tau_{\mathcal{A}}(t)}^{t} \big(\mathrm{p}_{\mathrm{h},\mathcal{A}}(V_{xy,\mathcal{A}}(t)) + \mathrm{p}_{\mathrm{v},\mathcal{A}}\big)\mathrm{d}t\,. \tag{4}$$

Let us consider N aircraft in a space $\mathbf{S}$. At the macroscopic level, the time is discretized according to an aggregation time Δt_{M}. Let κ, $\kappa = 1, 2, \ldots$, be the control time step and Δt_{M} the control sample time. For a time period $[(\kappa - 1) \cdot \Delta t_{\mathrm{M}}\,, \kappa \cdot \Delta t_{\mathrm{M}})$, the energy consumption for the whole network $\mathrm{E}(\kappa)$ $[\mathrm{aircraft} \cdot \mathrm{Wh}]$ can be aggregated according to the energy consumption of aircraft $\mathrm{E}_{\mathcal{A}}(\kappa), \mathcal{A} \in 1, \ldots, N$, as follows,

$$\mathrm{E}(\kappa) = \sum_{\mathcal{A} \in \mathbf{S}} \mathrm{E}_{\mathcal{A}}(\kappa)\,. \tag{5}$$

The aggregation equation (5) highlights that the energy consumption is influenced by the aircraft speed (or the flight travel time) in the network. Hence, it would be interesting to explore the relationship between the energy consumption E and the average speed V in the network.

C. Preliminary exploration of macroscopic energy modeling and control methodologies

The accumulation-based model uses the outflow-MFD, $G(n)$, which is a function of accumulation n, i.e., the number of aircraft in the network, and describes the evolution of accumulation as

$$\dot{n}(t) = d(t) - G(n(t))\,, \tag{6}$$

where $n(t)$ [aircraft] represents the number of aircraft in the network at time t, while $\dot{n}(t)$ [aircraft/s] represents its time derivative. $d(t)$ [aircraft/s] denotes the inflow rate of planned aircraft trips, and $G(n(t))$ [aircraft/s] denotes the outflow rate. According to simulation results in [5], the LAAT MFD shape is a nonsymmetric unimodal curve, where n_c [aircraft] is the critical accumulation that avoids congestion and corresponds to G_{m} [aircraft/s].

The objective of this study is to regulate the network inflow by managing the entry times of aircraft into the network. The control input, denoted as $u(t)$ $[-]$, determines the ratio of the inflow $d(t)$ [aircraft/s] that enters the network at a given time t. According to (6), the controlled aircraft mass conservation equation is as follows,

$$\dot{n}(t) = d(t) \cdot u(t) - G(n(t))\,. \tag{7}$$

In-ground traffic literature, many traffic control strategies aim at maximizing the system efficiency by determining an objective to maximize outflow G in the network. According to the outflow-MFD $G(n)$, this can be achieved by minimizing the error between the critical accumulation n_c to the current accumulation $n(t)$, i.e., $n_c - n(t)$. Hence, one criterion in the objective function of the optimal control problem can be formulated as follows,

$$J_0 = \|n_c - n(t)\|^2\,. \tag{8}$$

Nonetheless, such a criterion J_0 does not take into account that the control input might exacerbate the traffic condition with larger queues outside the network or within the network in specific locations while aiming for system optimum. Additionally, J_0 aims to operate around the critical point, though, when the system is in undersaturated condition, i.e., $n(t) < n_c$, it is essential to minimize the delay caused by the control input, as in such condition the system might not be in congestion. Therefore, it is possible to add an additional element which aims to minimize the error between the control input $u(t)$ to a control reference value u_{r}. Then, the revised criterion can be formulated as follows

$$J_1 = \omega_n \cdot \|n_c - n(t)\|^2 + \omega_u \cdot \|u_{\mathrm{r}} - u(t)\|^2\,, \tag{9}$$

where ω_n and ω_u are weighting factors. One can formulate an optimal control problem with objective J_1, see (9), and derive a control strategy that maximizes outflow, namely *PO*.

The goal of the current paper is to utilize the LeM method for minimizing the energy consumption in the LAAT network. Given the relation between speed V and aggregate energy consumption $\mathrm{E}(V)$ (results are shown later on in Section III), and the relation between accumulation n and speed $V(n)$, one can model the aggregate energy consumption as $\mathrm{E}(V(n))$ and add it in the objective as follows:

$$J_2 = \omega_{\mathrm{E}} \cdot \mathrm{E}(V(n)) + J_1\,, \tag{10}$$

where ω_{E} is a weighting factor. As a result, a control strategy that aims to operate around the critical point, i.e., aiming to maximize outflow, along with aiming to minimize energy consumption, represented by objective J_2 given in (10), can be derived, namely *POE*.

Additionally, another control strategy can be derived that only aims to minimize energy consumption in the network, namely *PE*, as follows,

$$J_3 = \omega_{\mathrm{E}} \cdot \mathrm{E}(V(n)) + \omega_u \cdot \|u_{\mathrm{r}} - u(t)\|^2 . \tag{11}$$

Overall, the optimal control problem for a gating policy while utilizing LeM is formulated as follows,

$$\min_{u(t)} \quad J(\mathrm{E}, n, u) = \int_0^{t_{\mathrm{f}}} \Big(\omega_{\mathrm{E}} \cdot \mathrm{E}(V(n)) + \omega_n \cdot \|n_{\mathrm{c}} - n(t)\|^2 + \omega_u \cdot \|u_{\mathrm{r}} - u(t)\|^2 \Big) \mathrm{d}t \tag{12}$$

s.t.

Eq. (7)

$$0 \leq n(t) \leq \overline{n} \,, \tag{13}$$

$$\underline{u} \leq u(t) \leq \overline{u} \,, \tag{14}$$

$$n(0) = n_0 \,. \tag{15}$$

The state and control input are bounded in this problem: First, the accumulation $n(t)$ $[\mathrm{aircraft}]$ has a lower bound of zero, and the upper bound is the maximum accumulation $\overline{n}$ $[\mathrm{aircraft}]$, see (13). In addition, the control input $u(t)$ $[-]$ has a lower bound $\underline{u}$ $[-]$ and an upper bound $\overline{u}$ $[-]$, see (14). Lastly, n_0 is the initial accumulation value, see (15). To conclude, the objective function (12) is minimized subject to the dynamic (7), the constraints (13) and (14), with the initial value (15).

In this paper, the outflow rate $G(n(t))$ is an estimated function

$$G(n(t)) = (\frac{v_{\mathrm{m}}}{a_{\mathrm{G},1}}) \cdot n(t) \cdot (e^{-a_{\mathrm{G},2} \cdot (\frac{n(t)}{a_{\mathrm{G},3}})^{a_{\mathrm{G},4}}}) , \tag{16}$$

where $a_{\mathrm{G},1}$, $a_{G,2}$, $a_{G,3}$, $a_{G,4}$, $a_{\mathrm{G},5}$ are the estimated parameters from curve fitting. Additionally, the macroscopic energy consumption rate $\mathrm{E}(V(n))$ is defined according to the estimated function

$$\mathrm{E}(V) = (\frac{v_{\mathrm{m}}}{a_{\mathrm{E},1}}) \cdot (e^{-(\frac{V}{a_{\mathrm{E},2}})^{a_{\mathrm{E},3}}}) , \tag{17}$$

where $a_{\mathrm{E},1}$, $a_{\mathrm{E},2}$, $a_{\mathrm{E},3}$ are the estimated parameters from curve fitting. And the relationship $V(n)$ is defined as follows

$$V(n) = (\frac{v_{\mathrm{m}}}{a_{\mathrm{V},1}}) \cdot (e^{-a_{\mathrm{V},2} \cdot (\frac{n}{a_{\mathrm{V},3}})^{a_{\mathrm{V},4}}} + a_{\mathrm{V},5}) , \tag{18}$$

where $a_{\mathrm{V},1}$, $a_{\mathrm{V},2}$, $a_{\mathrm{V},3}$, $a_{\mathrm{V},4}$, $a_{\mathrm{V},5}$ are the estimated parameters from curve fitting.

The optimal control problem, expressed by Eqs. (12)–(15), is solved with a Model Predictive Control (MPC) approach. The MPC feedback loop handles model-plant errors. The MPC controller determines the optimal control sequence for the current horizon $\mathbf{N}_{\mathrm{p}}$ by optimizing the prediction accumulation-based model. The model is a discrete formulation of Eqs. (12)–(15), discretized with a time step of Δ_{k} $[\mathrm{s}]$.

An aircraft command system is a crucial component that applies the Model Predictive Control (MPC) solution at the microscopic level to control the aircraft, such as regulating routing, speed, and other critical variables. In this study, based on the feedback control strategy, the aircraft command system determines the entrance time of each aircraft to the network, ensuring optimal utilization of airspace resources.

The MPC controllers optimize the optimal control input $u(t)$ for the macroscopic level. The control input is transformed to waiting times for aircraft entrance, Δt_{e}. Thus, the entrance times of aircraft $t_{\mathrm{e},\mathcal{A}}$ are updated by adding Δt_{e}, i.e., $t_{\mathrm{e},\mathcal{A}} \leftarrow t_{\mathrm{e},\mathcal{A}} + \Delta t_{\mathrm{e}}$. This transformation is proportional to the control step Δt_{C}, and Δt_{e} is bounded between 0 and $t_{\mathrm{f}} - t$ as follows,

$$\Delta t_{\mathrm{e}} = \min\big(\max\big(0, \Delta t_{\mathrm{C}} \cdot (1 - u(t))\big), t_f - t\big) . \tag{19}$$

III. SIMULATION RESULTS

To diagnose energy consumption in LAAT network and to examine the proposed LeM methodology, the LAAT-Flow simulation environment, see [5], *is extended to include aircraft energy consumption model* [2]. The additional settings are described in Section III-A. To develop LeM, one needs first to identify the airspace behavior via traffic characteristics estimation. The identification methodology and results are presented in Section III-B. Furthermore, to demonstrate the potential behind LeM, a simplified case study with the application of a gating policy comparing different objectives is presented in Section III-C.

A. Simulation setup

Different settings and inputs are required to set the computation to perform the traffic analysis, such as aircraft, airspace, and traffic and simulation settings. These inputs are fed to the plant model, the control model, and the controllers. It is possible to conduct a wide range of analyzes and studies of the plant model's outputs, but in this study, our main interest is the aircraft trajectories and speeds. The aircraft trajectories construct the MFD variables, and the aircraft speeds construct the LeM variables. Additional information from the plant model is used for the aircraft command system, such as the aircraft status (departing, traveling, arriving, and queuing) and the aircraft entrance time. It is noteworthy that the LAAT-Flow simulation [5] can effectively simulate the traffic characteristics of LAAT systems using different algorithms, aircraft settings, and airspace settings. Hence, the simulation settings for the following case study are resolved to explore ECM and LeM for low-altitude airspace.

The simulation setup and settings are similar to the one used in [5], [6], where in this study case, the airspace network is considered as a one-layer one-region 3D network where flight is allowed on the X-Y-Z plane and the network area is set to be 1.5 $[\mathrm{km}]$ by 1.5 $[\mathrm{km}]$ by 80 $[\mathrm{m}]$.

[2] Supporting data, code, and the simulation software are available from the authors upon reasonable request via the website [8].

Additionally, the aircraft energy consumption model described in Section II-B requires additional settings related to the aircraft design with the environment coefficient. In this study, the following values are chosen based on [9]: the drag coefficient C_D is 0.025 $[-]$, the rotor radius b is 0.25 $[\mathrm{m}]$, the front-facing area A is 0.2 $[\mathrm{m}^2]$, the total weight of the aircraft (including the battery, payload, and frame) W is 3.5 $[\mathrm{kg}]$. Additionally, the air density can be approximated as $D = 1.2$ $[\mathrm{kg/m}^3]$ and the gravity coefficient as $g = 9.8$ $[\mathrm{N}]$.

B. Identification results

This case study example is presented to construct LeM curves for a LAAT system. The case study is evaluated from different simulation scenarios (up to 20 runs), as each scenario has a different maximum inflow rate in the traffic inflow $q(t)$ profile, where the maximum inflow rate value q_{m} varies from 1800 $[\mathrm{aircraft/hr}]$ to 36000 $[\mathrm{aircraft/hr}]$ (0.5 $[\mathrm{aircraft/s}]$ to 10 $[\mathrm{aircraft/s}]$). Each point is an aggregated value of 60 $[\mathrm{s}]$ of simulated data.

From traffic control perceptive, it is interesting to model the relation between the accumulation n and outflow $G(n)$, as observed in Fig. 3(a), we estimate the following relation: $G(n) = (\frac{20}{681}) \cdot n \cdot e^{(-1.47 \cdot ((\frac{n}{1000})^{0.68}))}$, with the critical point (n_c, G_m) equals to $(954$ $[\mathrm{aircraft}], 6.8$ $[\mathrm{aircraft/s}])$. Additionally, the relation between the accumulation n and speed $V(n)$ is essential to deriving the LeM. As observed in Fig. 3(b), we estimate the following relation: $V(n) = (\frac{20}{1.24}) \cdot (e^{(-1.07 \cdot ((\frac{n}{1000})^{1.02}))} + 0.07)$.

The goal of this paper is to explore how the aggregate energy consumption in the network E is related to the speed V. This relation is presented in Fig. 3(c). Intuitively, the results show that as the number of aircraft increases, so does the energy consumption, and when the speed decreases, the energy consumption also increases. The key contribution of this research is the ability to determine the relationship between speed V, and energy consumption $\mathrm{E}(V)$. We have derived the following equation to describe this relationship: $\mathrm{E}(V) = (\frac{20}{8.204803e{-}04}) \cdot (e^{(-\frac{V}{2})} + 0.02)$, where the energy consumption E_{ss}, i.e. the corresponding energy consumption at the critical accumulation, is determined as 824.9 $[\mathrm{aircraft} \cdot Wh]$.

C. Preliminary results for gating policy based on LeM

The proposed gating policy, as introduced in Section II-C, is implemented in the simulation based on the identification results presented in Section III-B. Three control strategies are tested and compared to a no control (NC) scenario: (PO) aiming to maximize outflows, see (8), (PE) aiming to minimize energy consumption, see (11), and (POE) aiming to achieve a balance between outflow maximization and energy minimization, see (10).

In the simulation, the control strategies are evaluated under the same settings as the no control scenario, where the average inflow rate is set to $q_m = 7.5$ $[\mathrm{aircraft/s}]$ (representing an oversaturated condition). The weighting factors for the objective function $J(\star)$, see (12), are determined for each strategy as follows: (PO) $\omega_{\mathrm{E}} = 0$ $[-]$, $\omega_n = 1/n_c$ $[1/\mathrm{aircraft}]$, $\omega_u = n_c$ $[\mathrm{aircraft}]$; (PE) $\omega_{\mathrm{E}} = 1$ $[-]$, $\omega_n = 0$ $[-]$, $\omega_u = \mathrm{E}_{ss}$ $[\mathrm{aircraft} \cdot \mathrm{Wh}]$; and (POE) $\omega_{\mathrm{E}} = 1$ $[-]$, $\omega_n = \mathrm{E}_{ss}/{n_c}^2$ $[\mathrm{Wh/aircraft}]$, $\omega_u = \mathrm{E}_{ss}$ $[\mathrm{aircraft} \cdot \mathrm{Wh}]$.

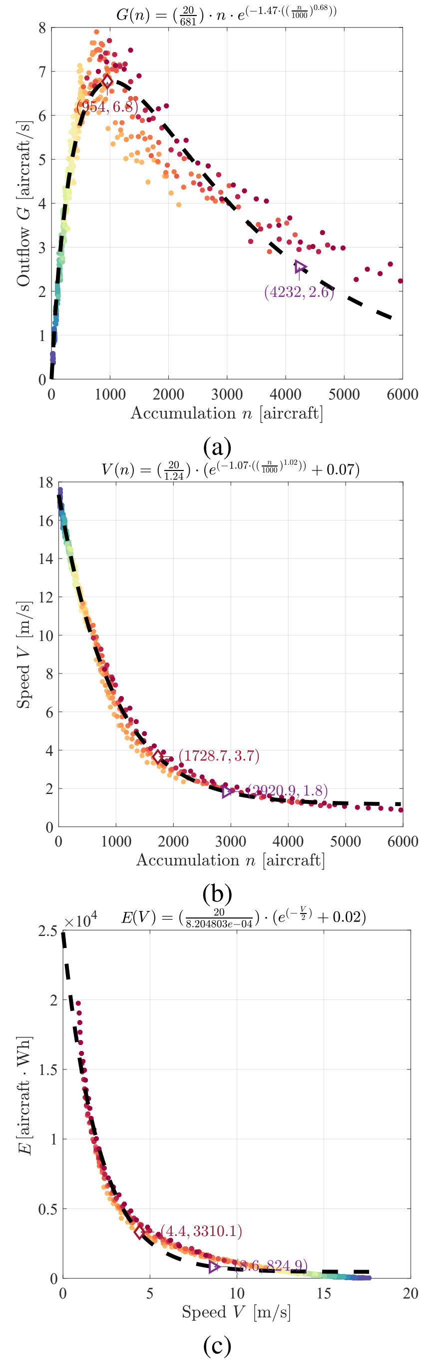

Fig. 3. Simulation results: (a) Outflow G vs. Accumulation n, (b) Speed V vs. Accumulation n (c) Aggregated energy consumption in the network E vs. Speed V. (Colormap represents different scenarios with different maximum inflow rate values $q_{\mathrm{m}} = \{0.5, \ldots, 10$ $[\mathrm{aircraft/s}]\}$).

Fig. 4 and Fig. 5 present the simulation results, comparing the different control strategies. Fig. 4(a) presents the Total Traveled Time (TTT) for each control strategy, while Fig. 4(b) presents the total energy consumption in the network for traveling aircraft (E). The results show that all control strategies lead to a reduction in both TTT and E. However, PO shows a relatively smaller decrease in TTT and E compared to PE and POE strategies.

It should be stressed that the results in Fig. 4 considers only the traveling aircraft inside the network, without taking into account the queuing aircraft outside (waiting to enter). To account for this vital aspect, we further analyzed the Total Time Spent (TTS) and the corrected total energy consumption (E^*) for both traveling and queuing aircraft, as presented in Fig. 5. The results clearly demonstrate that POE excels in system performance, as it does not only enhance efficiency for traveling aircraft within the network but also mitigates the negative impact on queuing aircraft. In contrast, PE, while showing positive results for the inside network, seems to exacerbate the situation for queuing aircraft, making it a less balanced approach compared to POE.

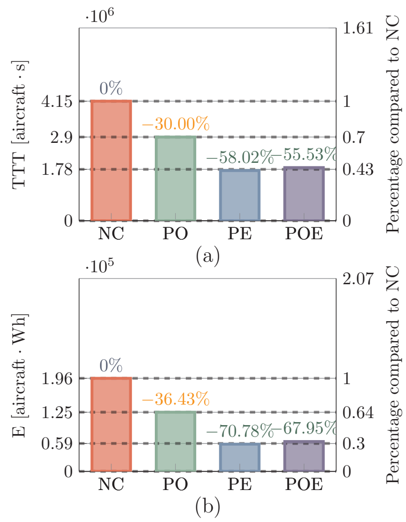

Fig. 4. Simulation results for comparing different control strategies, (NC,PO,PE,POE): (a) Total Traveled Time (TTT), (b) Total energy consumption in the network for traveling aircraft.

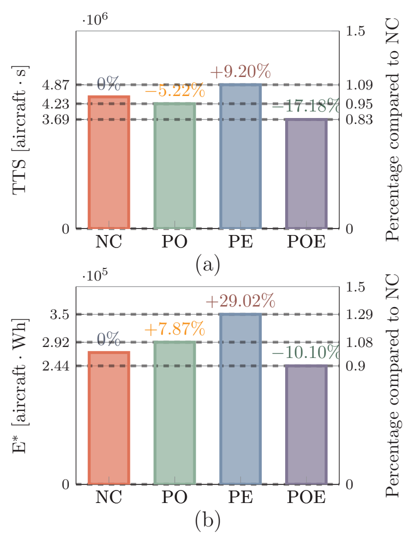

Fig. 5. Simulation results for comparing different control strategies, (NC,PO,PE,POE): (a) Total Time Spent (TTS), (b) Total energy consumption in the network for traveling and queuing aircraft.

IV. Summary and Concluding Remarks

This paper introduces sustainable aspects of low-altitude air city transport (LAAT) systems and investigates aircraft energy consumption in air mobility (AM) operations. To address this crucial concern, we develop the LAAT Energy Consumption Model (LeM) by integrating an aircraft energy consumption model (ECM) into the LAAT model-based operational framework. The LeM allows us to model the complex relationship between energy consumption and speed in LAAT networks, enabling the design of traffic control strategies that consider network energy consumption.

The presented simulation results, comparing various control strategies (PO, PE, and POE), deliver promising outcomes for enhancing efficiency and sustainability in LAAT systems. Significantly, the POE approach demonstrates distinguished performance, balancing outflow maximization and energy consumption minimization to the advantage of both traveling and queuing aircraft. These insights provide invaluable guidance for designing effective traffic control strategies and optimizing LAAT systems.

To advance this research field, future studies could explore a variety of aircraft types to account for the diverse landscape of low-altitude aircraft in AM operations. Improving the accuracy of the energy consumption model by incorporating real-world flight data and considering variations in flight conditions would further strengthen the reliability of LeM.

As a follow-up research, it is essential to investigate the application of LeM in more advanced traffic control designs, leveraging cutting-edge modeling methods to explore more significant efficiency and sustainability in AM operations.

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