ODEL: an On-Demand Edge-Learning framework exploiting Flying Ad-hoc NETworks (FANETs)

G. M. Cappello[1], G. Colajanni[1], P. Daniele[1], L. Galluccio[2], C. Grasso[2], G. Schembra[2], L. Scrimali[1]
[1]DMI, University of Catania - [2]DIEEI, University of Catania and CNIT Research Unit - Italy
name.surname@unict.it

ABSTRACT

[1] The evolution of smart objects towards the Internet of Softwarized Things (IoST) in 6G networks will provide the society with dynamic and programmable systems of interconnected smart devices interacting with little to no human intervention. One pivotal aspect of this evolution is represented by edge learning, which brings machine-learning algorithms at the network edge to achieve massive connectivity, ultra-low latency, energy efficiency, security and privacy. Unfortunately, in many application scenarios commonly envisioned for 6G, edge learning is not feasible neither locally in the smart objects, due to their computation and energy limitations, nor by servers at the edge of the cabled network, because not connected with adequate powerful links. To this purpose, this paper proposes ODEL, an On-Demand Edge-Learning framework that uses a Flying Ad-hoc NETwork (FANET) to bring computing and networking facilities on-site for edge learning. ODEL is based on a marketplace employing a non-cooperative game theoretic approach: UAVs are provided by different third-party providers in exchange of some economic gain. A non-linear optimization problem is formulated in order to determine the optimal distribution of flows that maximizes revenue for each UAV provider, and is solved by means of the Variational Inequality (VI) theory.

CCS CONCEPTS

• **Computing methodologies** → **Modeling methodologies**; • **Networks** → **Network economics**; • **Computer systems organization** → **Cloud computing**.

KEYWORDS

Edge Learning, 6G, IoST, UAVs, Marketplace.

ACM Reference Format:
G. M. Cappello[1], G. Colajanni[1], P. Daniele[1], L. Galluccio[2], C. Grasso[2], G. Schembra[2], L. Scrimali[1]. 2023. ODEL: an On-Demand Edge-Learning framework exploiting Flying Ad-hoc NETworks (FANETs) . In *The Twenty-fourth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing (MobiHoc '23), October 23–26, 2023, Washington, DC, USA.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3565287.3618259

[1]This work was partially supported by the European Union under the Italian National Recovery and Resilience Plan (NRRP) of NextGenerationEU, partnership on "Telecommunications of the Future" (PE00000001 - program "RESTART"). The research was partially supported also by the PIACERI project "OMNIA", the GNAMPA-INdAM Group, the PRIN Project "Liquid_Edge", and the POR S6 project. G. Colajanni was also partially supported by the MUR and the EU for the PON project on Research and Innovation 2014-2020, D.M. 1062/2021. C. Grasso was supported by European Union (NextGeneration EU), through the MUR-PNRR project SAMOTHRACE (ECS00000022).

MobiHoc '23, October 23–26, 2023, Washington, DC, USA

ACM ISBN 978-1-4503-9926-5/23/10…$15.00
https://doi.org/10.1145/3565287.3618259

1 INTRODUCTION

As we approach the third decade of the 21st century, the evolution of wireless communication technologies has empowered with huge connectivity and data capabilities. At the forefront of this progress lies the vision for the sixth generation (6G) of wireless networks, bringing a technological leap that promises to transcend the boundaries of its predecessors and usher in groundbreaking advancements [1]. 6G is foreseen to transform the conventional communication-centric paradigm into a communication-computing data-centric system, empowering a significant shift towards network intelligence. With a visionary approach, 6G will move intelligence from centralized cloud and edge infrastructure to user devices, granting users seamless access to a variety of services, anytime and anywhere [2]. The rise of smart objects, commonly known as Internet of Things (IoT) devices, represents a remarkable technological advancement that will be enabled by 6G systems, facilitated by the network softwarization paradigm that leads to the evolution towards the Internet of Softwarized Things (IoST) [3]. In the context of 6G, zero-touch approach will allow these devices to autonomously collect, process, and exchange data, unlocking endless possibilities for innovative applications and services [4]. However, to fully embrace the potential of IoST in 6G, certain challenges must be met, including massive connectivity, ultra-low latency, energy efficiency, enhanced sensing and perception, security and privacy [5].

One pivotal aspect of this evolution is to train machine learning algorithms at the network edge. This mechanism is typically denoted as *edge learning* [6, 7]. By diverging from traditional centralized machine learning, edge learning distributes the training and inference processes to geographically distributed edge devices and servers.

Unfortunately, in many application scenarios commonly envisioned for 6G [8], smart objects are neither connected to the network infrastructure nor connected to the power grid. This way, edge learning is not feasible neither locally in the smart objects, due to their computation and energy limitations, nor in servers at the edge of the cabled network, because not connected with adequate powerful links. To this purpose, this paper proposes ODEL, an On-Demand Edge-Learning framework relying on use of Flying Ad-hoc NETworks (FANETs) to bring computing and networking facilities where needed, on-site, to implement edge learning [9–11]. The FANET is composed by a certain number of UAVs, each equipped with a computing element (CE), so being able to process data flows coming from smart objects for model training. Given the time variability of the need for UAVs, this paper proposes to model ODEL as a marketplace employing a non-cooperative game theoretic approach: UAVs are provided by different third-party providers in exchange of some economic gain. A challenging aspect associated with the use of UAVs is their limited computational and energy resources. The problem of UAV battery charge duration is even exacerbated by the presence of the CE that represents one of the main causes of energy consumption which, when CE has to perform model training, can be comparable with what is required by engines.

In recent years there has been a growing interest in proposing cooperative and non-cooperative game theoretic approaches to model networking problems in the perspective of FANETs [12, 13]. In this paper, we formulate a nonlinear optimization problem in order to determine the optimal distribution of flows that, for each provider, maximizes its revenue while satisfying some constraints. The formulated optimization problem for the above market is described by means of the Variational Inequality (VI) theory. [14, 15].

The rest of the paper is organized as follows. In Section 2 we present the proposed ODEL framework. Then, in Section 3, we illustrate the ODEL management policy that allows UAV providers to decide the amount of flow coming from IoST to accept for learning. Section 4 formulates the problem by means of the VI theory, while Section 5 presents and analyzes some illustrative numerical examples. Finally, Section 6 draws some conclusions and discusses future work.

2 THE ODEL FRAMEWORK

The ODEL framework that is proposed in this paper is sketched in Fig. 1. Its objective is to provide edge learning service on demand to smart objects that are not able to perform machine learning locally for computing and energy limitations. To this purpose, for privacy reasons and considering that in many relevant scenarios, the smart objects are badly connected or not connected at all to the cabled network, a FANET is in charge of performing model training from the data flows coming from those smart objects, so avoiding to send big or private data streams to remote servers. More specifically, the FANET maintains one model for each aggregated data stream, i.e., for each set of homogeneous smart objects.

In order to characterize the edge learning service requested to the FANET, for each set k of smart objects, let us define the amount of computation, s_k, needed to process a single data unit (DU) for learning (for example, a DU can be an image or a video clip). The terms s_k is defined as the mean number of FLoating point OPerations (FLOP) required to process each DU.

Let ODEL be managed by an entity called the *ODEL Manager*. When it receives a request for edge learning, it creates a FANET with a number Q of *Learning Server UAVs* (LS-UAV). The goal of each LS-UAV is to participate in the learning process by training local models from the DUs coming from some sets of homogeneous smart objects. We denote as $\overline{C}_q$ the computational capacity of the computing element mounted onboard of the LS-UAV q.

LS-UAVs are owned by third-party UAV providers that participate in the FANET in exchange of some economic revenue. Specifically, the provider of each LS-UAV applies a price to the amount of learning operations it performs. Since model training is a heavy task

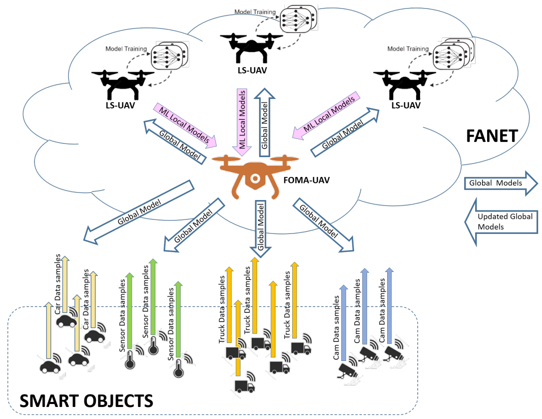


Figure 1: ODEL Reference Model

in terms of computing complexity and energy consumption, each stream of DUs coming from a set of homogeneous smart objects is distributed among different LS-UAVs of the FANET.

Besides the LS-UAVs, another UAV is included in the FANET, named the *FANET Orchestrator and FL Model Aggregator* (FOMA-UAV). It is owned by the ODEL Manager. The FOMA-UAV is in charge to orchestrate the FANET and assigning data streams coming from the smart objects to the LS-UAVs according to the management policy described in Section 3. In addition, it is in charge of updating the global models (one for each set of homogeneous smart objects) according to a Federated Learning (FL) approach, by using the local models received by the LS-UAVs. Each time the FOMA-UAV updates a model, it sends this not only to the relevant set of smart objects to perform the required smart functions, but also to both the LS-UAVs in the FANET to be used for future learning, and to an external model aggregator for a higher level of FL with other FANETs.

Let K be the number of sets of homogeneous smart objects. For example, in Fig. 1, $K = 4$ sets of smart objects are served by a FANET consisting of $Q = 3$ LS-UAVs. We denote as $k = 1, \dots, K$ a specific learning service required for the set k of smart objects, and as $q = 1, \dots, Q$ the generic LS-UAV in the FANET. Each LS-UAV, for each learning service, can decide the portion of data rate that it intends to process. In addition, once a LS-UAV has accepted a given portion of data rate to be processed, it can delegate the execution of part of it to other LS-UAVs, so acting as *Delegating Server*. Moreover, we refer to *Delegated Servers* as the LS-UAVs that receive this load.

3 ODEL MANAGEMENT POLICY

Let us now present in detail the management policy of the ODEL framework. First we define the most relevant variables needed to represent ODEL, i.e. y_{kq} and $x_{kq\tilde{q}}$. The variable y_{kq} describes the amount of data rate of the flow generated by the set k of smart objects and accepted to be processed for learning by the LS-UAV q. Instead, $x_{kq\tilde{q}}$ is the amount of the flow data rate coming from the set k of smart objects, accepted for training by the LS-UAV q, and delegated to the LS-UAV $\tilde{q}$, with $\tilde{q} \neq q$.

In order to simplify the notation, let us introduce the index sets $\mathcal{I}^{(Q)} = \{1, \dots, q, \dots, Q\}$ and $\mathcal{I}^{(\mathcal{K})} = \{1, \dots, k, \dots, K\}$. Moreover, we define the compact arrays and matrices of the above variables. More specifically, for the variable y_{kq}, we define:

$$Y_k^{(K)} = (y_{kq})_{q \in \mathcal{I}^{(Q)}}; \quad Y_q^{(Q)} = (y_{kq})_{k \in \mathcal{I}^{(\mathcal{K})}}; Y = (y_{kq})_{\substack{k \in \mathcal{I}^{(\mathcal{K})} \\ q \in \mathcal{I}^{(Q)}}} \quad (1)$$

that represent, respectively, the portions of flows managed by all the LS-UAVs for the set k of smart objects, the ones managed by the LS-UAV q for all the sets of smart objects, and all the portions of flows for all the sets of smart objects and for all the LS-UAVs.

Likewise, for the variables $x_{kq\tilde{q}}$, we define:

$$X_{q\tilde{q}} = (x_{kq\tilde{q}})_{k \in \mathcal{I}^{(\mathcal{K})}}; \quad X_q = (x_{kq\tilde{q}})_{\substack{k \in \mathcal{I}^{(\mathcal{K})} \\ \tilde{q} \in \mathcal{I}^{(Q)}}};$$

$$\tilde{X}_q = (x_{k\tilde{q}q})_{\substack{\in \mathcal{I}^{(\mathcal{K})} \\ \tilde{q} \in \mathcal{I}^{(Q)}}}; \quad X = (x_{kq\tilde{q}})_{\substack{k \in \mathcal{I}^{(\mathcal{K})} \\ q, \tilde{q} \in \mathcal{I}^{(Q)}}} \quad (2)$$

that represent the portions of flows generated by all sets of smart objects and accepted for management, respectively, by the LS-UAV q and delegated to $\tilde{q}$, by LS-UAV q and delegated to any other LS-UAV, by any LS-UAV and delegated to the LS-UAV q, and by any LS-UAV and delegated to any other LS-UAV.

If we denote the cumulative data rate coming from the set k of smart objects as D_k, it is evident that the following conservation law must be satisfied:

$$\sum_{q=1}^{Q} y_{kq} = D_k, \quad \forall k \in \mathcal{I}^{(\mathcal{K})}. \quad (3)$$

Moreover, let us define W_{kq} as the amount of flow k actually served by the LS-UAV q. Hence, W_{kq} is given by the amount of the flow k initially accepted for service by q, and added of a term that considers both the flow delegated by q to other LS-UAVs and the one that q is delegated by other LS-UAVs on its turn:

$$W_{kq} = y_{kq} + \sum_{\substack{\tilde{q}=1 \\ \tilde{q} \neq q}}^{Q} (x_{k\tilde{q}q} - x_{kq\tilde{q}}). \quad (4)$$

An important element to be considered in the ODEL framework is the fligth duration of each LS-UAV, that is limited by the UAV energy constraints. In fact, when the battery of a LS-UAV is exhausted, it is forced to temporarily leave the FANET to charge or substitute its battery, so loosing some economic gains. For this reason, each LS-UAV provider q sets a lower bound, Δ_q, for the flight duration δ_q of its UAV. More specifically, δ_q depends not only on its battery capacity, but also on the consumed power. This is given by the sum of the power used by the engines, $P_q^{(En)}$, the power used by the CE in the idle state, i.e. when it is not performing any computation, $P_q^{(CE)}$, and the power consumed to provide learning services, $P_q^{(S)}$. This is the term that influences the management policy since it depends on the computational load the LS-UAV q is performing. It can be calculated as the sum, for each learning service k, of its complexity, expressed in FLOPs, multiplied by the total DU rate processed for that service:

$$P_q^{(S)} = e^{(E)} \sum_{k \in \mathcal{I}^{(\mathcal{K})}} s_k W_{kq}, \quad (5)$$

where $e^{(E)}$ is the elementary energy consumption, defined as the energy needed to process one FLOP.

Therefore, we have that δ_q is given by:

$$\delta_q = \frac{B}{P_q^{(En)} + P_q^{(CE)} + e^{(E)} \sum_{k \in \mathcal{I}^{(\mathcal{K})}} s_k W_{kq}}. \quad (6)$$

Concerning prices and costs, let us characterize them as follows:

- ρ_{kq} is the price applied by the LS-UAV provider q for managing a unit of flow data rate coming from the set k of smart objects. As usual in market models [16], it depends on the overall data rate of the executed flows for that learning service $Y_k^{(K)}$, that is:

$$\rho_{kq} = \rho_{kq}\left(Y_k^{(K)}\right), \ \forall k \in \mathcal{I}^{(\mathcal{K})}, \ \forall q \in \mathcal{I}^{(Q)}, \quad (7)$$

  and it is assumed to be continuous, continuously differentiable, and decreasing with y_{kq};
- $c_q^{(E)}$ is the total execution cost that the LS-UAV provider q pays for processing. It depends on the net flow data rate, ϕ_q, executed by the LS-UAV q. The term ϕ_q is given by the sum, for each learning service k, of the amount of flow data rates managed by the LS-UAV q but not delegated to other LS-UAVs and the amount of flow data rate that this LS-UAV has received as delegated for execution by other LS-UAVs, subtracted of the amount of data rate that this LS-UAV has delegated to other LS-UAVs. Therefore, we have:

$$\phi_q = \sum_{k \in \mathcal{I}^{(\mathcal{K})}} \Big(y_{kq} + \sum_{\substack{\tilde{q} \in \mathcal{I}^{(Q)} \\ \tilde{q} \neq q}} (x_{k\tilde{q}q} - x_{kq\tilde{q}})\Big). \quad (8)$$

  Accordingly, $c_q^{(E)} = c_q^{(E)}(\phi_q) = c_q^{(E)}\left(Y_q^{(Q)}, \tilde{X}_q, X_q\right)$;
- $c_{k\tilde{q}}^{(S)}$ is the total delegation cost that any LS-UAV provider has to pay to provider $\tilde{q}$ for the execution of the learning service k. It is associated with the flows sent by all the LS-UAVs to $\tilde{q}$ for all the requested learning services: $c_{k\tilde{q}}^{(S)} = c_{k\tilde{q}}^{(S)}(\tilde{X}_{\tilde{q}})$;
- $c_{kq}^{(M)}$ is the management cost that the LS-UAV provider q has to pay for managing the amount of flow data rate for the learning service k. It depends on the flow data rate accepted for that learning service: $c_{kq}^{(M)} = c_{kq}^{(M)}\left(y_{kq}\right)$;
- $c_{q\tilde{q}}^{(T)}$ is the transmission cost from the LS-UAV q to the LS-UAV $\tilde{q}$, and depends on the amount of delegated flows, for all the learning services, by q to $\tilde{q}$: $c_{q\tilde{q}}^{(T)} = c_{q\tilde{q}}^{(T)}\left(X_{q\tilde{q}}\right)$. Instead, when q is delegated by any other LS-UAV, we assume that the transmission cost is negligible for q.

In order to optimize the ODEL management policy, for each LS-UAV provider q we introduce a utility function, which is given by the difference between the revenue and the overall cost incurred by that LS-UAV provider. More specifically, the revenue is obtained as the sum of unit demand prices of each learning service multiplied by the value of the flow data rate associated with the provision of each service managed by q, and the cost that all the other LS-UAV providers have to pay to q when it executes services managed by them. The overall cost is instead defined by the sum of all the execution costs for the provided services and for the ones additionally delegated by other LS-UAVs, the management cost and the transmission cost. Hence, the total utility function for the LS-UAV provider q is defined as:

$$U_q(X,Y)=\sum_{k=1}^{K}\rho_{kq}\left(Y_k^{(K)}\right)y_{kq}-c_q^{(E)}\left(Y_q^{(Q)},\tilde{X}_q,X_q\right)+$$
$$+\sum_{\substack{\tilde{q}=1\\ \tilde{q}\neq q}}^{Q}\left(c_q^{(S)}\left(\tilde{X}_q\right)\cdot\left(\sum_{k=1}^{K}x_{k\tilde{q}q}\right)-c_{\tilde{q}}^{(S)}\left(\tilde{X}_{\tilde{q}}\right)\cdot\left(\sum_{k=1}^{K}x_{kq\tilde{q}}\right)\right)+$$
$$-\left[\sum_{k=1}^{K}c_{kq}^{(M)}\left(y_{kq}\right)+\sum_{\substack{\tilde{q}=1\\ \tilde{q}\neq q}}^{Q}c_{q\tilde{q}}^{(T)}\left(X_{q\tilde{q}}\right)\right]. \quad (9)$$

Therefore, the ODEL management optimization problem for the LS-UAV provider q can be formalized as follows.

Determine the amount of data rate, y_{kq}, to accept for learning, the portion of y_{kq} to delegate to other LS-UAVs, $x_{kq\tilde{q}}$, and the portion of data rate associated to the learning service k, delegated by other LS-UAVs to it, $x_{k\tilde{q}q}$, in order to:

$$\text{maximize } \; U_q(X,Y) \quad (10)$$

subject to the following constraints:

- the conservation law regarding the demand D_k must be satisfied (without excesses or lacks):

$$\sum_{\tilde{q}\in\mathcal{I}^{(Q)}}y_{k\tilde{q}}=D_k,\quad \forall k\in\mathcal{I}^{(\mathcal{K})}; \quad (11)$$

- each LS-UAV cannot delegate to other LS-UAVs a portion of flow data rate that is higher than the one it is managing:

$$\sum_{\substack{\tilde{q}\in\mathcal{I}^{(Q)}\\ \tilde{q}\neq q}}x_{kq\tilde{q}}\le y_{kq},\quad \forall k\in\mathcal{I}^{(\mathcal{K})}; \quad (12)$$

- the computational resources required to manage all the flows accepted by the LS-UAV q must not exceed its maximum computational capacity:

$$\sum_{k=1}^{K}s_k\cdot W_{kq}\le\overline{C}_q; \quad (13)$$

- the flight duration of each LS-UAV q must be higher than a given threshold Δ_q imposed by the mission, i.e. $\delta_q>\Delta_q$. Therefore, according to the definition of δ_q in (6), we have:

$$\sum_{k\in\mathcal{I}^{(\mathcal{K})}}s_k\cdot W_{kq}\le\frac{B-\Delta_q\cdot\left(P_q^{(En)}+P_q^{(CE)}\right)}{e^{(E)}\cdot\Delta_q}; \quad (14)$$

- all the variables must be non-negative:

$$y_{kq},\ x_{kq\tilde{q}},\ x_{k\tilde{q}q}\ge 0,\quad \forall k\in\mathcal{I}^{(\mathcal{K})},\ \forall\tilde{q}\in\mathcal{I}^{(Q)}. \quad (15)$$

In addition, a general constraint in our system is represented by the hypothesis that a sufficient capacity is provided by the FANET as a whole, in order to satisfy all the service provisioning requests. Accordingly, we assume that:

$$\sum_{k\in\mathcal{I}^{(\mathcal{K})}}s_kD_k\le\sum_{q\in\mathcal{I}^{(Q)}}\overline{C}_q. \quad (16)$$

4 THE VARIATIONAL INEQUALITY FORMULATION

In this section, we provide the characterization of the optimization problem (10), subject to (11)-(15), by means of a variational inequality.

Let us assume that the demand price terms are continuously differentiable and concave, while all the cost terms are continuously differentiable and convex. Hence, the utility function is continuously differentiable and concave, and the feasible set is closed and convex. Therefore, the optimality conditions for all providers simultaneously are characterized by a variational inequality, as expressed by the following Theorem (for the proof, see [17]).

Theorem 1 (Variational Formulation). *A vector $(Y^*,X^*)\in\mathbb{K}$ is an optimal solution to the problem (10)-(15) if and only if there exist the Lagrange multiplier vectors $\mu^{(1)*}\in\mathbb{R}^K$, $\lambda^{(1)*}\in\mathbb{R}_+^{KQ}$ and $\lambda^{(2)*}\in\mathbb{R}_+^{Q}$ such that the vector $(Y^*,X^*,\mu^{(1)*},\lambda^{(1)*},\lambda^{(2)*})$ is a solution to the following variational inequality:*

$$\sum_{q=1}^{Q}\sum_{k=1}^{K}\Big[\frac{\partial c_q^{(E)}\left(Y_q^*,\tilde{X}_q^*,X_q^*\right)}{\partial y_{kq}}+\frac{\partial c_{kq}^{(M)}\left(y_{kq}^*\right)}{\partial y_{kq}}-\rho_{kq}\left(Y_k^*\right)-$$
$$+\frac{\partial\rho_{kq}\left(Y_k^*\right)}{\partial y_{kq}}y_{kq}^*+\mu_k^{(1)*}-\lambda_{kq}^{(1)*}+s_k\lambda_q^{(2)*}\Big]\times(y_{kq}-y_{kq}^*)+$$
$$+\sum_{k=1}^{K}\sum_{\substack{q,\tilde{q}=1\\ \tilde{q}\neq q}}^{Q}\Big[\frac{\partial c_q^{(E)}\left(Y_q^*,\tilde{X}_q^*,X_q^*\right)}{\partial x_{kq\tilde{q}}}+\frac{\partial c_{q\tilde{q}}^{(T)}\left(X_{q\tilde{q}}^*\right)}{\partial x_{kq\tilde{q}}}+$$
$$+\lambda_{kq}^{(1)*}-s_k\lambda_q^{(2)*}\Big]\times(x_{kq\tilde{q}}-x_{kq\tilde{q}}^*)+$$
$$+\sum_{k=1}^{K}\sum_{\substack{q,\tilde{q}=1\\ \tilde{q}\neq q}}^{Q}\Big[\frac{\partial c_q^{(E)}\left(Y_q^*,\tilde{X}_q^*,X_q^*\right)}{\partial x_{k\tilde{q}q}}+s_k\lambda_q^{(2)*}\Big]\times(x_{k\tilde{q}q}-x_{k\tilde{q}q}^*)+$$
$$-\sum_{k=1}^{K}\Big[\sum_{q=1}^{Q}y_{kq}^*-D_k\Big]\times(\mu_k^{(1)}-\mu_k^{(1)*})+$$
$$-\sum_{k=1}^{K}\sum_{q=1}^{Q}\Big[\sum_{\tilde{q}=1}^{Q}x_{kq\tilde{q}}^*-y_{kq}^*\Big]\times(\lambda_{kq}^{(1)}-\lambda_{kq}^{(1)*})+$$
$$-\sum_{q=1}^{Q}\Big[\sum_{k=1}^{K}s_k\left[y_{kq}^*+\sum_{\substack{\tilde{q}=1\\ \tilde{q}\neq q}}^{Q}(x_{k\tilde{q}q}^*-x_{kq\tilde{q}}^*)\right]-\overline{C}_q\Big]\times$$
$$\times(\lambda_q^{(2)}-\lambda_q^{(2)*})\ge 0,$$
$$\forall\ (Y,X,\mu^{(1)},\lambda^{(1)},\lambda^{(2)})\in\mathbb{K}\times\mathbb{R}^K\times\mathbb{R}_+^{KQ}\times\mathbb{R}_+^{Q}, \quad (17)$$

where

$$\mathbb{K}=\{(Y,X)\in\mathbb{R}_+^{KQ^2}\ \mid(11)-(14)\ \textit{hold}\ \forall q\}. \quad (18)$$

Observe that VI (17) could easily be put in the following standard form (see [17]):
Find $Z^*\in\mathcal{K}\subseteq\mathbb{R}^N$ such that:

$$\langle F(Z^*),Z-Z^*\rangle\ge 0,\quad \forall Z\in\mathcal{K}\subseteq\mathbb{R}^N, \quad (19)$$

where $\langle\cdot,\cdot\rangle$ denotes the inner product in N-dimensional Euclidean space. Therefore, we now present an important result that concerns the existence and uniqueness of VI solution in eq. (17), based on the theory of variational inequalities (see [18]).

Theorem 2 (Existence and Uniqueness of VI solution). *A solution $Z^* \equiv (Y^*, X^*, \mu^{(1)*}, \lambda^{(1)*}, \lambda^{(2)*})$ to variational inequality (17) exists. Moreover, if the function $F(Z)$ as in (19), is strictly monotone, that is:*

$$\langle (F(\bar{Z}) - F(\tilde{Z})), \bar{Z} - \tilde{Z} \rangle > 0,$$

$$\forall \bar{Z}, \tilde{Z} \in \mathbb{R}_+^{KQ^2} \times \mathbb{R}^K \times \mathbb{R}_+^{KQ} \times \mathbb{R}_+^Q, \quad \bar{Z} \neq \tilde{Z}, \tag{20}$$

then, the solution Z^* is also unique.

5 NUMERICAL ANALYSIS

In this section, we present a numerical analysis of the ODEL framework applied to some relevant use cases. More specifically, we first describe the system setup and then, thanks to the VI approach introduced in Section 4 we derive the optimum configuration and system performance in the considered scenarios.

Let ODEL FANET be composed by $Q = 3$ LS-UAVs. The mean cumulative data rate coming from each set of smart objects are $D_1 = 35$, $D_2 = 40$, $D_3 = 20$ and $D_4 = 45$ DU/s, respectively. The amount of computation needed for learning to process a single DU is different for each service, specifically, we assume $s_1 = 2$, $s_2 = 10$, $s_3 = 3$ and $s_4 = 5$ kFLOPs [19].

The unit demand price functions, $\rho_{kq}(Y_k^{(K)})$, which are listed in Table 1, highlight the dependence of the price choice by each provider on the choices taken by the other providers. The other parameters, i.e. the execution, the transmission and the management cost functions are listed in Table 2. As concerns the characterization of UAV power consumption, we assume its engines absorb $P_q^{(En)} = 66$ W and the computing element $P_q^{(CE)} = 5.4$ W. Moreover, we consider an elementary energy consumption to provide the service, $e^{(E)} = 59.1 \cdot 10^{-3}$ J/FLOP, and a battery capacity $B = 50$ Wh.

As previously mentioned, in our analysis, we consider the two following scenarios:

1. *Resource-Constrained* (RC) scenario, characterized by LS-UAVs each with a CE capacity of 264 kFLOP/s; therefore, the overall FANET capacity is of 792 kFLOP/s;
2. *Over-Provisioned* (OP) scenario, characterized by LS-UAVs each with a CE capacity of 352 kFLOP/s; therefore, the overall FANET capacity is of 1056 kFLOP/s.

In both scenarios, as imposed in (16), the total FANET capacity, that is the sum of the maximum capacities for all the LS-UAVs, is greater than the total request of services, given by $\sum_{k=1}^K s_k D_k$. The name assigned to the above scenarios is given by the comparison of the total computation capacity provided by the FANET in each scenario and the overall load provided by the input flows, that is $\sum_k D_k \cdot s_k = 755$ kFLOPs.

By solving the Variational Inequality in (17), we obtain the optimal solutions, that is the k-service request that each provider q satisfies, the portion of service requests to delegate to and delegated by other LS-UAVs, at the equilibrium. Hence, we could determine $U_q(X^*, Y^*)$, the total utility for each provider, calculated in the optimal solutions and the flight duration actually used by each LS-UAV. We analyze each of these aspects by varying $\overline{C}_1$, $\overline{C}_2$ and $\overline{C}_3$, i.e. the available computational resource of LS-UAVs $q = 1$, $q = 2$ and $q = 3$, respectively. We change $\overline{C}_q$ in a range between 228 kFLOP/s and 300 kFLOP/s in the RC scenario, while we change it in a range between 316 kFLOP/s and 400 kFLOP/s in the OP scenario.

Figs. 2a, 2b and 2c show the utility functions of each provider. Each colour represents a provider (blue, green and red for provider $q = 1$, $q = 2$ and $q = 3$, respectively), while the dashed and the solid lines refer to the RC and the OP scenarios, respectively. For all the simulations, and in both the RC and OP scenarios, provider $q = 1$ has the highest utility, instead, the other two providers are switched in the two scenarios ($q = 2$ has the higher utility in RC scenario, and $q = 3$ in OP scenario). Except for provider $q = 2$, providers obtain a higher utility in OP scenario than in RC.

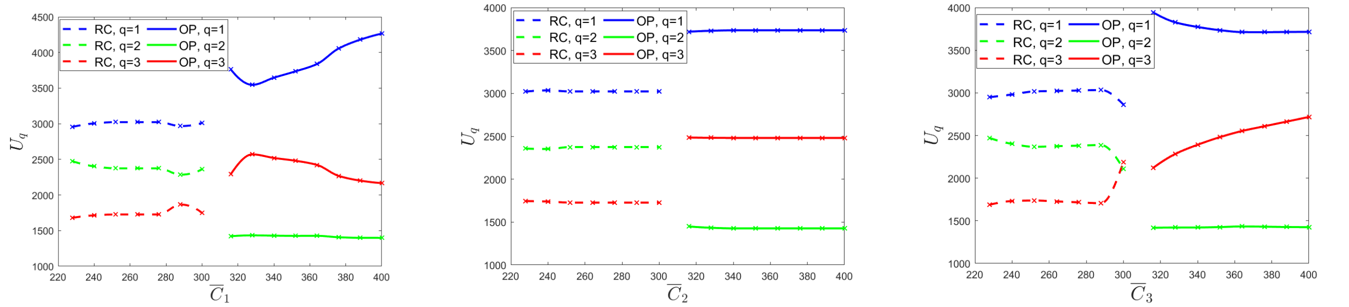
For both scenarios, Figs. 3a, 3b and 3c show the results related to the flight duration of the LS-UAVs. From the figures, we can appreciate that, thanks to the application of our optimization framework, they result to be almost comparable. An exception is, as expected, for provider $q = 2$ in scenario OP that does execute few services, and consequently it has the greatest flight duration. As shown by Fig. 3a, when the LS-UAV provider $q = 1$ increases computational resources, it has a decreasing flight duration. Similarly, when the computational resources of LS-UAV $q = 3$ are increasing (in both scenarios), it has a decreasing flight duration (see Fig. 3c). Instead, by varying $\overline{C}_2$ (see Fig. 3b), except for very small amounts of computational resources, the flight duration, as well as the utility function, remains almost constant. Clearly, when the values of the computational resources of all LS-UAVs are equivalent (i.e., 264 kFLOP/s for the RC scenario and 352 kFLOP/s for the OP scenario), the points of the three graphs coincide (both for the utility function and the flight duration). Furthermore, the used computational resources have an opposite trend as compared to the flight duration.

Table 1: Unit demand prices.

$\rho_{11} = -0.3y_{11} + 2.2y_{12} + 2.3y_{13}$;	$\rho_{12} = -0.1y_{12} + 1.5y_{11} + 1.5y_{13}$;
$\rho_{13} = -0.2y_{13} + 1.1y_{11} + 1.2y_{13}$	$\rho_{21} = -0.1y_{21} + 1.1y_{22} + 2.3y_{23}$;
$\rho_{22} = -0.3y_{22} + 1.3y_{21} + 1.1y_{23}$;	$\rho_{23} = -0.1y_{23} + 1.3y_{21} + 1.1y_{22}$;
$\rho_{31} = -0.5y_{31} + 1.1y_{32} + 1.2y_{33}$;	$\rho_{32} = 1.7y_{31} - 0.5y_{32} + 2.0y_{33}$;
$\rho_{33} = 1.1y_{31} + 1.2y_{32} - 0.5y_{33}$;	$\rho_{41} = -0.2y_{41} + 1.3y_{42} + 1.5y_{43}$;
$\rho_{42} = 1.2y_{41} - 0.1y_{42} + 1.3y_{43}$;	$\rho_{43} = 1.1y_{41} + 1.3y_{42} - 0.3y_{43}$;

Table 2: Execution, transmission and management costs

Execution cost		
$c_1^{(E)} = 0.3 \cdot \phi_1^2 + 2 \cdot \phi_1$;	$c_2^{(E)} = 0.4 \cdot \phi_2^2 + 3 \cdot \phi_2$;	$c_3^{(E)} = 0.25 \cdot \phi_3^2 + 4 \cdot \phi_3$;
Transmission cost		
$c_{12}^{(T)} = 0.5(\sum_{k=1}^K x_{k12})^2 + (\sum_{k=1}^K x_{k12})$;	$c_{13}^{(T)} = 0.2(\sum_{k=1}^K x_{k13})^2 + (\sum_{k=1}^K x_{k13})$;	
$c_{21}^{(T)} = 0.09(\sum_{k=1}^K x_{k21})^2 + (\sum_{k=1}^K x_{k21})$;	$c_{23}^{(T)} = 0.35(\sum_{k=1}^K x_{k23})^2 + (\sum_{k=1}^K x_{k23})$;	
$c_{31}^{(T)} = 0.4(\sum_{k=1}^K x_{k31})^2 + (\sum_{k=1}^K x_{k31})$;	$c_{32}^{(T)} = 0.45(\sum_{k=1}^K x_{k32})^2 + (\sum_{k=1}^K x_{k32})$;	
Management cost		
$c_{11}^{(M)} = 0.2y_{11}^2 + 0.1y_{11}$;	$c_{12}^{(M)} = 0.1y_{11}^2 + 0.5y_{11}$;	$c_{13}^{(M)} = 0.3y_{13}^2 + 0.1y_{13}$;
$c_{21}^{(M)} = 0.2y_{21}^2 + 0.2y_{11}$;	$c_{22}^{(M)} = 0.5y_{22}^2 + 0.1y_{22}$;	$c_{23}^{(M)} = 0.25y_{22}^2 + 0.2y_{23}$;
$c_{31}^{(M)} = 0.2y_{31}^2 + 0.2y_{31}$;	$c_{32}^{(M)} = 0.4y_{32}^2 + 0.1y_{32}$;	$c_{33}^{(M)} = 0.35y_{33}^2 + y_{33}$;
$c_{41}^{(M)} = 0.25y_{41}^2 + 0.5y_{41}$;	$c_{42}^{(M)} = 0.25y_{42}^2 + y_{42}$;	$c_{43}^{(M)} = 0.35y_{43}^2 + 2y_{43}$

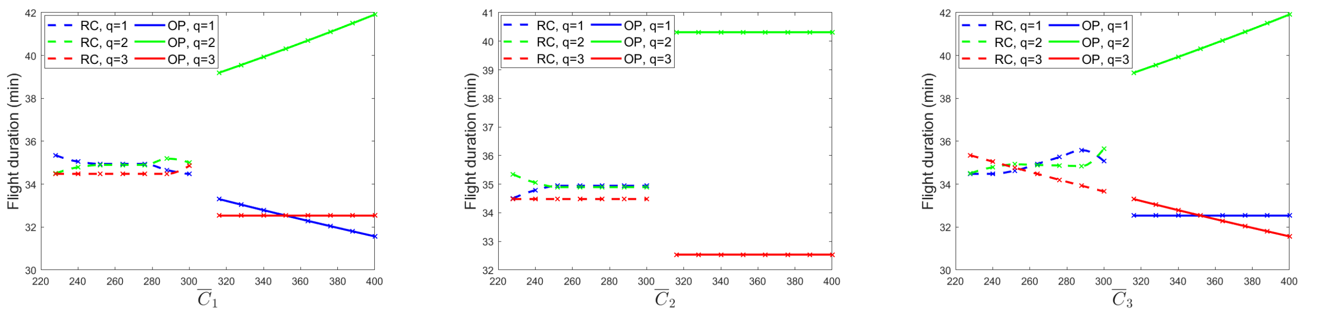


(a) U_q **vs.** $\overline{C}_1$

(b) U_q **vs.** $\overline{C}_2$

(c) U_q **vs.** $\overline{C}_3$

Figure 2: Utility function (U_q) of each provider



(a) Flight duration vs $\overline{C}_1$

(b) Flight duration vs $\overline{C}_2$

(c) Flight duration vs $\overline{C}_3$

Figure 3: Flight duration of each provider

6 CONCLUSIONS AND FUTURE WORKS

In this paper, we propose ODEL, an On-Demand Edge-Learning framework that uses a Flying Ad-hoc NETwork (FANET) to bring computing and networking facilities on-site for edge learning. The ODEL Manager creates the FANET with a number of LS-UAV that are provided by different providers according to a marketplace approach, with the objective of maximizing their profits. The goal of each LS-UAV is to participate in the learning process by training local models from the DUs coming from some sets of homogeneous smart objects. A non-linear optimization problem is formulated in order to determine the optimal distribution of flows that maximizes revenue for each UAV provider, and is solved by means of the VI theory. As future work, we are working on extending the present non-cooperative game to a scenario of coalitions among LS-UAV providers, and analyzing the system in a long-term horizon, considering dynamic changes in the number of LS-UAVs.

REFERENCES

[1] J. Wei, H. Bin, H. M. Asif, and H. D. Schotten. The road towards 6G: A comprehensive survey. *IEEE Open Journal of the Communications Society*, 2, 2021.
[2] Q. Li and *et al.* 6g cloud-native system: Vision, challenges, architecture framework and enabling technologies. *IEEE Access*, 10:96602–96625, 2022.
[3] M. Adil and *et al.* Iost: Internet of softwarized things networks, security challenges and future research directions. In *2022 IEEE Globecom Workshops*, pages 269–274.
[4] C. Grasso, R. Raftopoulos, and G. Schembra. Smart zero-touch management of uav-based edge network. *IEEE Transactions on Network and Service Management*, 19(4):4350–4368, 2022.
[5] C. Grasso and G. Schembra. Design of a uav-based videosurveillance system with tactile internet constraints in a 5g ecosystem. In *IEEE NetSoft 2018*, 2018.
[6] C. Mung and T. Zhang. Fog and iot: An overview of research opportunities. *IEEE Internet of Things Journal*, 3(6):854–864, 2016.
[7] S. Wang and *et al.* When edge meets learning: Adaptive control for resource-constrained distributed machine learning. In *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, pages 63–71, 2018.
[8] Next G Alliance Report: 6G Applications and Use Cases. http://web.archive.org/web/20080207010024/http://www.808multimedia.com/winnt/kernel.htmhttps://www.nextgalliance.org/white_papers/6g-applications-and-use-cases/.
[9] F. Pasandideh, J. P. J. da Costa, R. Kunst, N. Islam, W. Hardjawana, and E. Pignaton de Freitas. A review of flying ad hoc networks: Key characteristics, applications, and wireless technologies. *Remote Sensing*, 14(18), 2022.
[10] C. Grasso, R. Raftopoulos, G. Schembra, and S. Serrano. H-home: A learning framework of federated fanets to provide edge computing to future delay-constrained iot systems. *Computer Networks*, 219:109449, 2022.
[11] C. Grasso, R. Raftopoulos, and G. Schembra. Slicing a fanet for heterogeneous delay-constrained applications. *Computer Communications*, 195:362–375, 2022.
[12] S. D'Oro and *et al.* A game theoretic approach for distributed resource allocation and orchestration of softwarized networks. *IEEE JSAC*, 35(3):721–735, 2017.
[13] S. Lasaulce and H. Tembine. *Game theory and learning for wireless networks: fundamentals and applications.* Elsevier, 2011.
[14] A. Nagurney. *Network Economics: A Variational Inequality Approach.* Springer Science & Business Media, 1998.
[15] J.-S. Pang F. Facchinei. *Finite-Dimensional Variational Inequalities and Complementarity Problems.* Springer Science, 2003.
[16] A. Nagurney and *et al.* A supply chain network equilibrium model. *Transportation Research Part E: Logistics and Transportation Review*, 38(5):281–303, 2002.
[17] A. Nagurney. *Network Economics: A Variational Inequality Approach, second and revised edition.* Springer New York, NY, 1999.
[18] D. Kinderlehrer and G. Stampacchia. *Variational inequalities and their applications.* New York, Academic Press, 1980.
[19] J. Sevilla, L. Heim, M. Hobbhahn, T. Besiroglu, A. Ho, and P. Villalobos. Estimating training compute of deep learning models, 2022. Accessed: 2023-8-2.