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RESEARCH ARTICLE

# A D2D-Aided Federated Learning Scheme With Incentive Mechanism in 6G Networks

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**ABSTRACT** Pervasive new era applications are expected to involve massive amount of data to implement intelligent distributed frameworks based on machine learning, supported by sixth generation (6G) networks technology to offer fast and reliable communications. Federated Learning (FL) is rapidly emerging as promising privacy-preserving solution to train machine learning models in a distributed fashion. However, users are often not too inclined to take part in the learning process without receiving compensation. Hence, to overcome this drawback, the functional integration of a proper devices incentive mechanism with an efficient approach for the devices selection in a same FL framework becomes essential. In this regard, this paper proposes a FL framework involving a one-side matching theory-based incentive mechanism to select and encourage users to take part of the process with the aim at minimizing the FL process convergence time and maximizing the users profit. Furthermore, this paper faces with the possibility to overcome bad communication link conditions by resorting to device-to-device communications among users in order to lower the energy wasted and improve the convergence time of the FL process. In particular, an echo-state-network, running in local at each user site, has been considered to forecast channel conditions in a reliable manner. Performance evaluation has highlighted the improvements in convergence time and energy consumption of the proposed FL framework in comparison with conventional approaches, hence, highlighting its suitability for applications in the upcoming 6G networks.

**INDEX TERMS** Federated learning, terahertz communications, machine learning.

## I. INTRODUCTION

The efforts towards the progressive standardization of 6G networks are focusing on enabling different types of network services and new era applications guaranteeing high-performance ubiquitous and intelligent connectivity, preserving data privacy and security [1], [2]. The upcoming 6G networks will be empowered by artificial intelligence capabilities, in order to providing efficient and effective strategies to transmit, collect, merge, manipulate and interpret large amount of data, anytime and anywhere, to support disruptive applications and intelligent services, shifting the development of wireless communications from ''connected things'' to ''connected intelligence'' [1], [2]. Recent years have seen the unprecedented involvement of data science, machine and deep learning solutions into a wide plethora of applications. Nevertheless, the machine learning (ML), together with the 6G network technology, is promising to boost the new generation systems. Nowadays, there exist two major obstacles in making the ML oriented solutions a concrete reality [3]: *i*) data are typically private by some legal concern or by the general data protection regulation (GDPR), making users the exclusive owner of their data. In fact, traditional ML solutions, implemented on a central server, give rise to several privacy and security issues. Moreover, centralized solutions suffer also of severe communication, processing and aggregation overhead, making infeasible their application to large-scale scenarios; *ii*) the rapidness with which terahertz (THz) channel conditions vary over time, typically due to blockage events, capturing the phenomenon in which the Line-on-Sight (LoS) signal between the considered user and its corresponding base station is interrupted [4]. All these difficulties represent critical aspects which prevent the actual diffusion of pervasive and secure intelligent frameworks supported by 6G

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networks [1]. Despite these drawbacks, decentralized learning paradigms are recently gaining momentum, representing flexible solutions to keep private data locally at the origin device, training there the ML model and reducing the amount of information to send to the central server. In particular, Federated Learning (FL) has emerged as promising learning paradigm and as an efficient alternative to the centralized ML solutions. The FL represents a collaborative decentralized learning framework, in which devices and a central server mutually interact to train a shared model [5], [6]. The shared model is downloaded from the central server by devices which train the model with local data, and then upload to the server the results of their local computation. In this way devices send to the central server only local model updates instead of raw data [5], [6], realizing a cooperative training for a group of users, whereas the obtained model can be exploited by any device belonging to the network [7]. Finally, it is important to highlight the fact that devices are typically energy constrained, hence, a FL deployment that lowers the energy waste is of paramount importance and a main challenge here.

Despite a large part of the literature on this subject is based on the hypothesis that once the devices have been selected to take part to the FL framework they have unconditionally participate to it, this cannot be longer considered now as a practical assumption in real-world application scenarios. In particular, from a user's perspective, commitment of resources and the intention to be involved in the FL process have to be both considered.[1] Within this picture, an incentive mechanism is proposed here in order to induce users to participate to the FL framework. More specifically, this paper focuses on a 6G network in which a combined ML and matching theory (MT) framework has been developed to incentive users to take part in the learning process. Furthermore, a suitable users selection criteria based on the channel conditions forecasting to all users has been proposed. Hence, the salient contributions of the paper can be summarized as follows

- Usage of an echo state network (ESN), located at each user site, to forecast the channel propagation conditions, aiming at lowering the negative impact of bad channel propagation conditions on the FL process both in terms of convergence time and energy wasted.
- Development of a matching game to suitably select the devices to be involved in the FL process. In particular, such a selection process is performed on the basis of the channel predictions provided by the ESNs. In this reference, it is important to point out that bad channels conditions suffered by the devices may drastically impact the success of the FL procedure, resulting in slow convergence time or unexpected delays. Note that, for the best of authors' knowledge, this is the first paper that takes into account in the devices selection process the quality of the 6G channel and considers the opportunity to resort to a D2D communication mode, as an alternative, to counteract FL process degradations.
- In-depth performance analysis of the proposed framework, in comparison to a vanilla approach, and to the case where the auction-based incentive mechanism, proposed in [8], has been considered as an alternative.

The rest of the paper is organized as follows. In Section II an in-depth review of the related literature is provided. Section III presents the system model description, while Section IV proposes the ESN-based forecasting approach to predict the channel conditions. Likewise, Section V deals with the proposed matching theory approach. Performance evaluations are presented in Section VI and, finally, our conclusions are drawn in Section VII.

## II. RELATED WORKS

Many papers in recent literature have dealt with the FL paradigm and highlighted its privacy advantages. Some examples are represented by [9], [10], [11], [12], and [13]. In particular, in [9] the traffic classification problem was addressed by proposing a secure federated transfer learning model based on the deep learning paradigm and applying the cross-silo horizontal technique to preserve privacy and security. Furthermore, specific FL features were deeply analyzed in [10], where a FL architecture was optimized, in order to test and evaluate the effective potentials of the FL technology, also in terms of privacy preservation. In [11] Deng et al. discussed the applicability of the blockchain technology to the FL framework, proposing a trading platform in which users are able to sell the personal data and the local computation resources. In particular, authors in [11] provided a framework demonstration taking into account the users authenticity verification, consistency of the model updates, and support to scale the distributed applications. Paper [12] investigates the application of the federated learning to blockchains, aiming at minimizing the network load. Then, the resources-awareness was the subject discussed in [13], where the devices resources availability was considered, together with the users activities monitoring, in order to perform FL on the basis of the realistic world setting. Moreover, paper [13] proposed a discard policy to exclude the untrustworthy users from the batch of users taking part to the learning process, whenever an incorrect model was injected by users. The FL was also applied in [14] to support the training needed to handle mobile reconfigurable intelligent surfaces (RISs) and the users power allocation, aiming at improving channel quality, spectrum efficiency and users data rate. Non-orthogonal multiple access techniques were exploited, and a deep-reinforcement learning strategy was applied to optimize the performance. Differently, in [15] the focus was on a hybrid learning environment, considering both the centralized and the FL paradigms, in order to use the most suitable learning modalities on the basis of the context. Furthermore, in [16], a suitable formulation in terms of an integer linear programming problem was proposed to minimize social cost. In particular, it was highlighted in [16] that

[1] In what follows, with the aim at simplified notation, users and devices will be used interchangeably.

the corresponding complexity results to be NP-hard. Then, a proper discipline was proposed in [16] to decide the devices participating to the FL process, as well as how to schedule the participation of winners and the number of global iterations. The authors in [17] considered an edge computing scenario arranged to support tasks offloading. Moreover, the FL was applied to forecast the execution time of the edge server in the asymmetrical information environment considered, on the basis of which the delay energy product metric was optimized performing proper offloading strategies. The problem of the incentive users considering their contributions was addressed in [18], where authors developed a framework based on the Gale-Shapley value to allocate proper incentives to participants. Once participants contributions have been measured, a users' reputation-driven reward allocation policy starts to distribute the incentive budget.

In [19] authors considered a multiaccess edge computing environment, in which the problem of the optimal task-device assignment in FL was addressed by resorting to a matching game with incomplete preferences, aiming at minimizing the resources cost. Similarly, paper [8] designed an auction mechanism to maximize the social welfare through the proper devices selection to be involved in the FL process. The strategy proposed is able to guarantee truthfulness, individual rationality and efficiency, also in terms of energy cost. Authors in [20] developed an incentive mechanism for the FL process to motivate edge nodes to take part in the model training. The incentive mechanism proposed is based on the exploitation of the deep reinforcement learning to identify the optimal pricing strategy for both the server and edge nodes. Paper [21] presented a privacy-preserving FL framework to realize mobile crowdsensing, in which cooperative game theory was applied to model the users marginal contributions and to design an incentive mechanism. Then, in [22], a matching theory based approach was proposed to select devices in order to minimize both the overall training time and the energy consumption, aiming at simultaneously identify unreliable devices, and integrating a reputation metric to guarantee reliability and trustworthiness.

Different from previous literature, this paper deals with an incentive mechanism without assuming ideal channel conditions. In fact, an ESN located on each device has been integrated in order to properly forecast the channel quality, integrating the possibility to perform device-to-device (D2D) communications when adverse channel conditions occur.

## III. SYSTEM MODEL

As reference scenario, we consider a network having connectivity compliant to the 6G technology at the THz frequencies by means of a small base station (SBS). Then, we have considered a set $\mathcal{M}$ of devices all able to be linked to the SBS and the presence of an aggregator $\mathcal{A}$, i.e., a central unit responsible for merging, interpreting or storing the data stemming from the network. Without loss of generality, to simplify the discussion, in this paper $\mathcal{A}$ coincides with the SBS, and it is assumed that $\mathcal{A}$ has a computational module equipped with a central processing unit (CPU) [23].

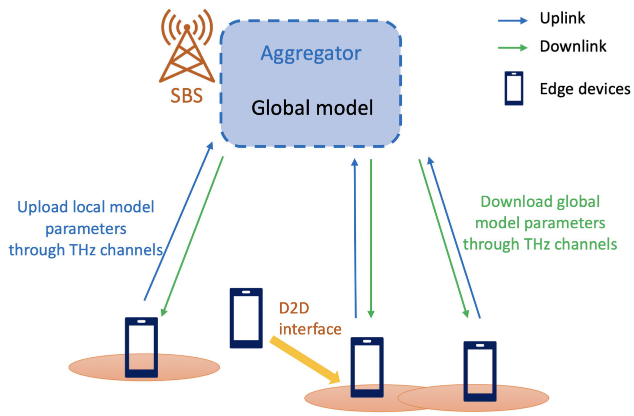


**FIGURE 1. FL system model.**

### A. FEDERATED LEARNING MODELS

As illustrated in Figure 1, the FL process, according to [24], [25], performs the training phase at the edge devices level. In particular, the FL process is iterative and articulated in global epochs, each of which consists of the following phases: 1) local computation; 2) model exchange; 3) central computation. During the first step, devices perform the local data training on the basis of a shared model download from $\mathcal{A}$. Each device $i$, belonging to the set $\mathcal{N} = \{1, \ldots, N\}$, with $\mathcal{N} \subset \mathcal{M}$, involved in the FL process has a dataset of individual data denoted with $D_i$, typically derived from the application usage of user $i$ (for example the response time of the device applications [26]). For each sample $j$ in $D_i$, the objective is to find a model parameter $w$ able to minimize the loss function $L_j(w)$. Therefore, each device $i$ has to solve the following minimization problem [26]

$$\min_{w} \mathcal{L}_i(w) = \frac{1}{|D_i|} \sum_{j \in D_i} L_j(w), \tag{1}$$

Hence, the corresponding learning model results to be the minimization of the following global loss function

$$\min_{w \in \mathbb{R}^e} \mathcal{L}(w) = \sum_{i=1}^{N} \frac{|D_i|}{\sum_{i=1}^{N} |D_i|} \mathcal{L}_i(w), \tag{2}$$

where $e$ denotes the input size. Consequently, during each local computation round $t$ of the FL framework, the device $i$ solve the local problem [26]

$$w_i^{(t)} = \arg\min_{w_i \in \mathbb{R}^e} F_i(w_i | w^{(t-1)}, \nabla \mathcal{L}^{(t-1)}), \tag{3}$$

where $F_i$ is the objective of user $i$, $w^{(t-1)}$ is the global parameter produced during the previous iteration, and $\mathcal{L}^{(t-1)}$ is the global loss function at time $(t-1)$. Once completing the local model training, each device $i$ uploads $w_i^t$ to $\mathcal{A}$ during the second step, in which $\mathcal{A}$ receives the devices weights.

On the other side, $\mathcal{A}$ possesses the global model that, during the step 3), is improved by performing the weighted average of the local updates $w_i^t$ previously uploaded by devices.

Therefore, in phase 3), $\mathcal{A}$ aggregates the received information and performs the following computations

$$w^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N} w_i^{(t)}, \tag{4}$$

and

$$\nabla\mathcal{L}^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N} \nabla\mathcal{L}_i^{(t)}, \tag{5}$$

Then, the iterative scheme is repeated, until a desired accuracy or the maximum number of iterations is achieved. Finally, it is important to stress that, due to its distributed nature, the FL process presents several advantages in terms of device privacy since local training is performed exclusively at the devices site.

### B. COMPUTATION AND COMMUNICATION MODELS

In our case, considering each device $i$ equipped with a CPU having working frequency $f_i$, given in number of CPU cycles per unit time, we have that the total computational capacity of device $i$ results to be $f_i$. Furthermore, let $\lambda_i$ be the percentage of occupied processing capacity,[2] we have that the available processing capacity results to be $(1-\lambda_i)f_i$ as in [7]. Likewise, the time spent by the device $i$ to perform the local model computation results in

$$t_i = \log\left(\frac{1}{\epsilon_i}\right)(1-\lambda_i)f_i D_i, \tag{6}$$

in which $\log\left(\frac{1}{\epsilon_i}\right)$ represents the number of local iterations needed to achieve the local accuracy $\epsilon_i$ that device $i$ can provide [7], [19].

Consequently, denoting with $p_i$ the power consumption of the $i$-th CPU, the associated energy consumption is

$$E_{t_i} = p_i \log\left(\frac{1}{\epsilon_i}\right)(1-\lambda_i)f_i D_i = p_i t_i. \tag{7}$$

Due to the local parameters uploading and to the global parameter broadcasting, communication cost has to be considered. Nevertheless, the uplink channel from the devices to $\mathcal{A}$ is exploited to transmit local parameters, in the downlink channel the global FL model is sent. In this paper, as in [8], we exclusively consider the uplink channel due to the relation of the uplink with the cost that user experiences during learning a global model. Moreover, we assume that each user has an individual access opportunity to the linked SBS (i.e., $\mathcal{A}$) with a negligible interference with all the others. Hence, in accordance with [4], [27], and [28], we have assumed an equal transmission power $P$ for all user and an equal data rate towards $\mathcal{A}$ given by:

$$\mathcal{R}_{\mathcal{A}} = \mathcal{W}\log_2\Big(1 + SNR_t\Big) \tag{8}$$

where $SNR_t$ denotes the lowest signal-to-noise ratio at the SBS site that assures a reliable data detection. Due to the high susceptibility of the THz channels to blockage phenomena, molecular absorption effects, and communication range, the quality of the communication channel conditions may have deep variations over time. As a consequence, we have here that whenever the instantaneous SNR at the SBS site falls below the $SNR_t$ a reliable data detection is denied. Within this picture, it will be highlighted later that the prediction of the communication channel conditions represents a useful tool to optimize the FL framework, lowering the possibility of data transmission failures due to communication channel conditions impairment.

Differently from previous solutions, in our case, whenever bad channel conditions are foreseen by the local ESN (Sec.IV), the interested user $i$ activates a D2D link towards an appropriate neighboring device properly selected as outlined in Sec. V-B using the same channel assigned to $i$ to communicate with $\mathcal{A}$. Moreover, a power level $P_D$ is used in order to allow a D2D data rate equal[3] to $\mathcal{R}_{\mathcal{A}}$.

Consequently, denoting with $v_i$ the local parameter size expressed in bits for user $i$, each communication round exhibits a cost in time defined as

$$\tau_i = \frac{v_i}{\mathcal{R}_{\mathcal{A}}}(x_{\mathcal{A}} + 2(1-x_{\mathcal{A}})) \tag{9}$$

in which $x_{\mathcal{A}}$ is a binary variable equal to 1 if device $i$ uses the direct link toward the aggregator $\mathcal{A}$, i.e., the cellular link, zero otherwise. From (9) follows that the energy consumption needed to transmit $v_i$ is

$$E_{\tau_i} = P\frac{v_i}{\mathcal{R}_{\mathcal{A}}}x_{\mathcal{A}} + \left(P_D\frac{v_i}{\mathcal{R}_{\mathcal{A}}} + P\frac{v_i}{\mathcal{R}_{\mathcal{A}}}\right)(1-x_{\mathcal{A}}), \tag{10}$$

where $P$ is the power transmitted by users. Note that, without loss of generality, we assumed the same power $P$ for all users. Therefore, considering the $i$-th device, the total amount of time spent in deriving the local updating $v_i$ and to send out it to $\mathcal{A}$, results in

$$T_i = t_i + \tau_i. \tag{11}$$

Likewise, the overall energy consumption is given by

$$E_{T_i} = E_{t_i} + E_{\tau_i}. \tag{12}$$

### C. USERS' REVENUE MODEL

From the aggregator point of view, in order to incentive users in taking part in the training process, a payment mechanism has to be included, aiming at encouraging the users involvement. To this regard, a concrete application example can be represented by the Google Keyboard [8]. Massive local data

[2] $\lambda_i$ represents the computational capacity occupied by background processes or other activities such as the ESN described in the next section.

[3] In order to simplify the discussion of the problem, we have assumed the same data rate for both the direct device to $\mathcal{A}$ and D2D communications.

are generated by users interacting with the keyboard app on their smartphones. Considering the Google server perspective, training a next-word prediction model based on users' data can be desirable. Consequently, the server can encourage the users' participation through advertisement pop-ups in the corresponding mobile phone app. When the user manifests an interest in the learning project sponsored by the Google Keyboard, the app will display an interface to submit the corresponding parameter and calculate the expected utility. Then, if the user confirms her/his interest in taking part in the project, she/he will download the dedicated app and a participation application will be submitted. Once the aggregator receives all proposals in a certain time, the aggregator will start the selection of the devices and then the training process by broadcasting an initial global model to all the winning users. After finishing the model training project, the aggregator will give users rewards (e.g., money) based on the bid it wins.

In this reference, we have assume here that each device $i$ has a given cost $\chi_i$ which varies on the basis of the availability of its hardware resources as the accuracy provided[4]

$$\chi_i = \mathcal{K} t_i, \tag{13}$$

in which $\mathcal{K}$ is the parameter which rules the amount of the user cost, that is the same for all the participants. As a consequence, the overall cost that aggregator $\mathcal{A}$ has to pay is $\sum_i \chi_i$. From the other hand, each user has a cost $\mu_i = E_{t_i}$, in taking part to the process, which implies that the utility of user $i$ is

$$\zeta_i = \left(\delta \chi_i - \mu_i\right). \tag{14}$$

Therefore, the corresponding overall utility is given by

$$\mathcal{U} = \sum_{i=1}^{N} \zeta_i b_i, \tag{15}$$

where $b_i = 1$ if user $i$ is selected to take part in the FL framework, zero otherwise. In addition, $\delta$ (J/sec) is a weight modeling an additional energy cost as in [26].

### D. PROBLEM FORMULATION

The optimization of the FL framework, is a multi-objective problem. In fact, if on the one hand the minimization of the mean time spent to converge,[5] i.e., the time needed to complete the model training, is crucial, also the maximization of the mean users' satisfaction in participating to the FL process is equally important, as discussed in [26]. Therefore, a proper trade-off between the convergence time and the users' satisfaction in participating to the FL process, must be guaranteed in order to properly perform the FL process. Therefore, the optimization problem under consideration has to jointly reach the following two objectives:

- minimization of the overall convergence time;
- maximization of the overall users' utility.

In formal terms, we have

$$\min_{\Gamma,\mathbf{X}} \frac{1}{N} \sum_{i=1}^{N} T_i \text{ AND } \max_{\Gamma,\mathbf{X}} \frac{1}{N} \mathcal{U} \tag{16}$$

$$s.t. \sum_i \chi_i b_i \leq B_{\mathcal{A}}, \tag{17}$$

$$\sum_{j=1}^{N+1} x_{i,j} = 1, \quad \forall i \in \mathcal{N} \tag{18}$$

$$\sum_{i=1}^{N} \gamma_i \leq N, \tag{19}$$

in which $\Gamma \in \{0, 1\}^N$ is the vector whose generic element is1 if device $i$ participates to the FL process, zero otherwise. Then, matrix $\mathbf{X} \in \{0, 1\}^{N \times N+1}$ represents the link selection matrix. Considering $i, j \in \{1, \ldots, N\}, i \neq j$, we have that the $x_{i,j}$ element of $\mathbf{X}$ is equal to 1 when device $i$ exploits the D2D interface to transmit towards the device $j$, or to zero, otherwise. In particular, we have $x_{i,N+1} = 1$ whenever the device $i$ communicates towards $\mathcal{A}$ throughout the direct link, hence, $x_{i,N+1} = 1$ means $x_{\mathcal{A}} = 1$ in (10) and (9). Furthermore, constraint (17) imposes that the overall cost payed by aggregator cannot exceed a given maximum available value $B_{\mathcal{A}}$. Similarly, constraint (18) points out that each user can enable only one communication interface, i.e., a direct link or a D2D interface. Finally, (19) denotes that the maximum number of users involved in the FL framework cannot exceed the actual number of users in the network.

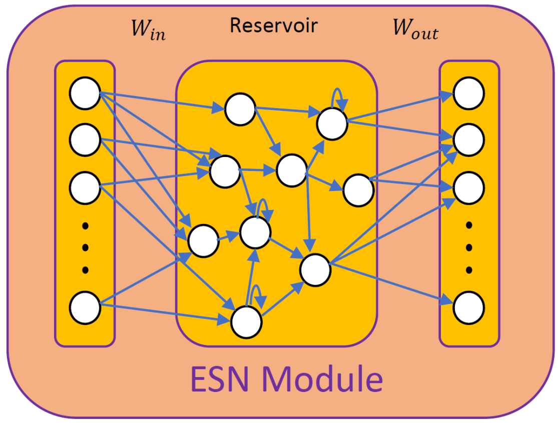


**FIGURE 2.** ESN architecture.

## IV. ECHO STATE NETWORK FOR CHANNEL FORECASTING

The power of the ESN resides in the fact that it represents an instance of the Reservoir Computing concept, inheriting the

[4]From a theoretical perspective, a more accurate functional cost may include the quality and the type of the channel exploited. In authors' opinion, this *a priori* knowledge is not a reasonable hypothesis considering practical applications.

[5]Note that by minimizing the convergence time, even the energy consumption is indirectly lowered due to the energy saving in both transmission and computation.

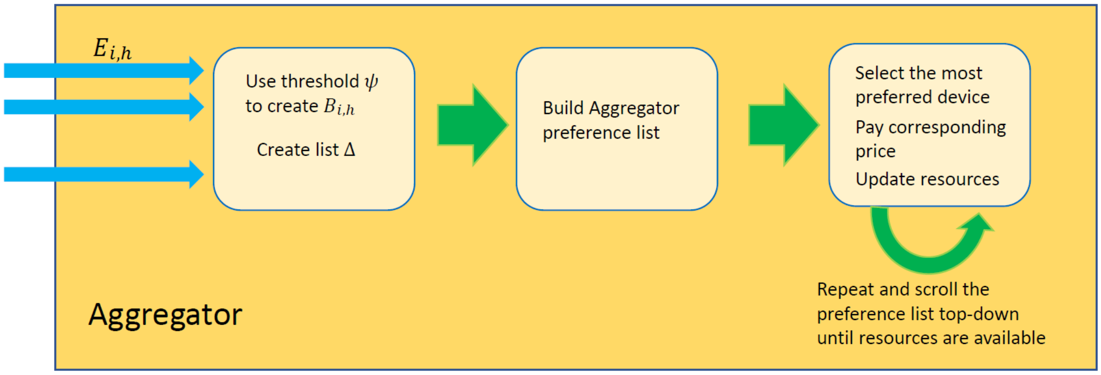


**FIGURE 3.** **Devices selection flow.**

benefits of recurrent neural network (RNN), such as the ability in processing inputs exhibiting time dependencies [29], without incurring in the typical problems affecting the training of RNNs, as the vanishing gradient issue, for example. Therefore, due to the low-complexity nature of the ESN, its implementation on board of devices belonging to $\mathcal{M}$ does not impact drastically the corresponding devices battery lifetime. In this paper, we have considered the impact of the ESN on the overall device activity as included in the percentage of occupied processing capacity expressed by $\lambda_i$. More in detail, as represented in Figure 2, the salient components of the ESN is given by the following four crucial aspects [29]

- neurons randomly connected;
- sparse connection links;
- large number of neurons;
- low in energy and time demand.

In accordance to [29], the ESN consists of three components: the input weight matrix $I$, the reservoir weight matrix $R$, and the output weight matrix $W$. We denote with $\mathbf{x}^{q\times 1}$ the input vector, assuming as reservoir weight matrix updating rule the following equation [29]

$$u^{s\times 1}(q) = \tanh(\mathbf{W}_{in}^{s\times q}\mathbf{x}^{q\times 1}(q) + \mathbf{W}_r^{s\times 1}(q-1)), \quad (20)$$

in which $u^{s\times 1}$ represents a vector of internal units in the reservoir part, and $\mathbf{W}_{in}^{s\times q}$ is the weights matrix associated to the connections existing between the input layer and the reservoir level. Then, the $\mathbf{W}_u^{s\times 1}(q-1)$ is the recurrent weights matrix. Denoting with $v(q)$ the output vector and $\mathbf{W}_{out}^{q\times s}$ the weight matrix associated to the connection between the reservoir and the output layer, the relationship between the reservoir and the output level can be described as

$$v(q) = \mathbf{W}_{out}^{q\times s}u^{s\times 1}(q). \quad (21)$$

Consequently, the ESN acts exploiting the historical channel samples $I$, to forecast the upcoming channel condition for each device $i \in \mathcal{N}$. Due to the temporal correlations between consecutive samples, the ESN may represent a significantly useful tool to predict channel conditions, due to its ability in catching temporal relationship among samples.

## V. MATCHING THEORY FOR DEVICES SELECTION

Matching theory (MT) is a powerful mathematical technique to match together elements belonging to two opposite sets, taking into consideration, during the assignment process, the satisfaction of each participant in being matched to each element of the opposite set and vice-versa, giving rise to an effective trade-off between the preferences exhibited by elements. In addition, another key advantage of the MT is its distributed nature, due to the fact that the matching process exclusively consider local utility metrics on the basis of which the individual preferences are built. Consequently, MT algorithms represent a valuable approach for distributed scenarios, such as the environment object of the analysis of this paper.

### A. DEVICES SELECTION

At the beginning of the proposed FL framework all the devices belonging to $\mathcal{M}$ send to $\mathcal{A}$ the channel predictions acquired by means of the local ESN as detailed below. Let $\mathcal{E}_{h,i}$ be the set of predicted channel state information coefficients considering as time horizon the instant $h$, i.e., $\mathcal{E}_{h,i} = \{e_{1,i}, \ldots, e_{h,i}\}$, in which $e_{y,i}$ is a binary term related to the $y$-th forecast sample ahead from the end of the training set used by the ESN on device $i$ at the step $y$, assuming the value 1 if the foreseen $SNR$ at the SBS site is greater or equal to $SNR_t$ or 0, otherwise. As illustrated in Figure 4, for each device $i$, $\mathcal{E}_{h,i}$ is sent to $\mathcal{A}$. Then, a threshold mechanism is applied to determine the number of times, before $h$, in which the channel has good state conditions. Such a counting procedure is articulated as follows. In formal terms, for each device $i \in \mathcal{M}$, $\mathcal{A}$ creates the following set

$$\mathcal{B}_{i,h} = \{e_{y,i} \in \mathcal{E}_{h,i} | e_{y,i} = 1\}. \quad (22)$$

Then, devices are collected and sorted in list $\Delta$, according to the number of ones belonging to sets $\mathcal{B}_{i,h}$, $\forall$ device $i \in \mathcal{M}$. At this point the one-side matching game algorithm [30] is applied between the set of devices $\mathcal{M}$, and the aggregator $\mathcal{A}$, in order to select devices for the FL process advantageous for all the players belonging to $\mathcal{M}$ and for $\mathcal{A}$ [30], [31].

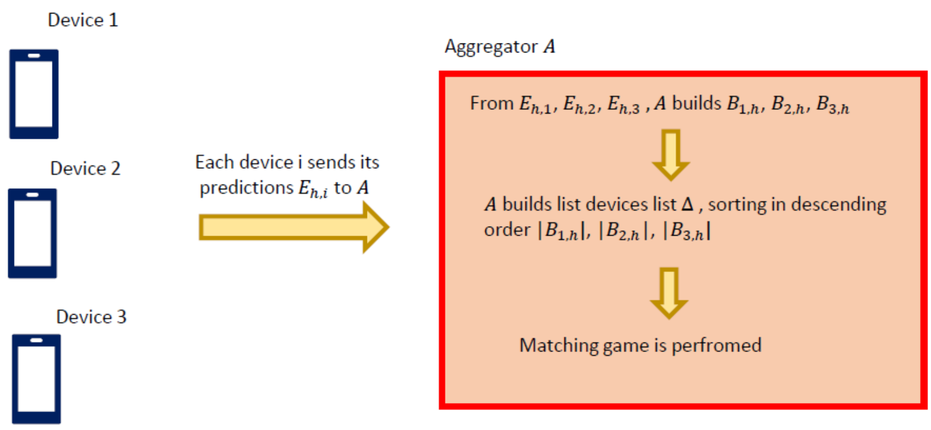


**FIGURE 4.** **Devices selection scheme.**

In this paper the preference lists of $\mathcal{A}$ over $\mathcal{M}$ represents the utility of the system in accepting the users for the federated training, considering also the users revenue. Therefore, the $\mathcal{A}$ preference list is build considering the following metric

$$H_{\mathcal{A}}(i) = \zeta_i \Big( N - \operatorname{rank}(i, \Delta) \Big), \tag{23}$$

for all device $i$ belonging to $\mathcal{M}$, where $\operatorname{rank}(i, \Delta)$ is the position of $i$ in list $\Delta$. Consequently, the most preferred device $i^*$ is given by

$$i^* = \arg \max_{i \in \mathcal{M}} H_{\mathcal{A}}(i). \tag{24}$$

The corresponding preference list is built sorting the devices in descending order on the basis of the $H_{\mathcal{A}}(i)$ value, $\forall i \in \mathcal{M}$. Then, scrolling the preference list top-down, $\mathcal{A}$ accepts all the device until $B_{\mathcal{A}}$ is not zero.

Summarizing, as also reported in Figure 3, the algorithm steps are the follows:

1) Each device $i \in \mathcal{M}$ performs the prediction of the channel state information (CSI) of the direct link towards the aggregator, $h$ steps ahead, exploiting the local ESN and sends this information to $\mathcal{A}$. The set $\mathcal{E}_{i,h}$ is created;
2) For each user $i \in \mathcal{M}$, $\mathcal{A}$ creates the sets $\mathcal{B}_{i,h}$, and creates the list $\Delta$ sorting the $\mathcal{B}_{i,h}$ sets in descending order on the basis of their cardinality;
3) $\mathcal{A}$ builds its preference list;
4) $\mathcal{A}$ selects the most preferred device $i^*$ from its preference list to take part in the FL process;
5) $\mathcal{A}$ pays $\chi_{i^*}$ to device $i^*$;
6) Update the available resources of $\mathcal{A}$: $B_{\mathcal{A}} - \sum_i \chi_i b_i$;
7) Delete $i^*$ from the preference list;
8) Repeat steps 5)-8) until $B_{\mathcal{A}} - \sum_i \chi_i b_i \geq b_{i^*}$ and there exists at least one device unselected.

Finally, to discuss the stability issue of the proposed matching approach, it is useful to refer to the following definition of the matching game stability:

*Definition 1:* A matching is stable when there is no player having incentive to deviate from the assignment to which it belongs to.

Moreover, we have to take into account that we have formulated here a one-sided matching game [30] between $\mathcal{M}$ and $\mathcal{A}$. As a consequence, as it is well-known from the literature [30], since the preference lists do not change during algorithm execution and the matching game is a one-sided matching, the final matching configuration has to be necessarily stable.

### *B. COOPERATIVE D2D DEVICE SELECTION*

Two cooperative D2D device selection procedures are presented below. As working hypothesis we have assumed that the number of devices selected to participate in the FL process is always lower than the total number of available devices. However, the special case of a number of selected devices equal to the overall available devices has been considered in deriving our simulation results in order to take into account its impact on the global FL delay and energy consumption.

- *Ideal D2D selection scheme*: Once the devices selection has been performed, $\mathcal{A}$ communicates to the selected devices their involvement in the FL process by a beacon signal that marks the start of the FL process. Successively, at the beginning of each FL round each involved device acquires an updated foreseen of the channel propagation condition towards $\mathcal{A}$ by the local ESN at the end of the current FL processing round. Whenever a bad condition is detected, the device starts the device discovery procedure searching among its nearby devices that one not involved in the FL process with no bad propagation conditions towards $\mathcal{A}$. Hence, the interested device starts a D2D communication to the selected device by making use of the channel allocated for communications to $\mathcal{A}$. The selected device in its turn sends the received update to the $\mathcal{A}$ on the same channel. In this way, no additional channel allocation by the SBS is needed and D2D interferences are avoided. If for a given device, suffering of bad propagation conditions, the device discovery procedure fails, i.e., no nearby device (if any) is able to support a D2D communication phase, the interested device skips the training step and, as a consequence, to transmit its update to $\mathcal{A}$, hence, avoiding an energy waste. Needless to say that this D2D selection scheme is ideal for obvious reasons that we avoid to discuss in detail here. However, it is also evident that it represents an ideal upper bound for the performance of the considered FL approach and, as a consequence, it will be considered as a benchmark in what follows.

- *SBS-Assisted D2D selection scheme*: differently form the previous ideal scheme, in which the D2D selection is performed runtime by each interested device during the FL execution, this procedure provides an *a priori* device selection performed by $\mathcal{A}$ after selection of the devices involved in the FL framework. In accordance with the proposed scheme, each device in $\mathcal{M}$ sends to $\mathcal{A}$ its set $\mathcal{E}_{h,i}$ and its location information. After completion of the matching game to select the devices taking part the FL (named hereafter as FL selected devices), as detailed in Section V-A, $\mathcal{A}$ searches for each FL selected device the nearest device not involved in the FL process as cooperating D2D host, to be exploited in case of foreseen bad quality conditions at the end of a FL round. In this case the beacon signal that marks the beginning of the FL process, in addition to the notification concerning the involvement of the FL selected devices in the FL process, carries also information about the possibility for each selected device to activate the D2D procedure and, in the positive case, the identification of the most suitable nearby device. Moreover, through the beacon signal all the devices selected to support D2D communications with the FL selected devices are informed about their their task and on the communication channel to be used for both the D2D communications and to send to $\mathcal{A}$ the received updated model information. It is important to note that each device can be elected as cooperating D2D host only for a FL selected device.[6] Moreover, in the case that no cooperating D2D hosts was found for a given FL selected device, the D2D procedure for that device is denied and the training step as well the update transmission to $\mathcal{A}$ are skipped, in order to prevent an energy waste. As for the ideal D2D selection scheme outlined before, the D2D as well as the next selected cooperative device to $\mathcal{A}$ data updated transmission are performed on the same channel allocated to the interested FL involved device.

### C. SUMMARY OF THE PROPOSED SOLUTION

The aim of this subsection is to retrace the main steps of the framework proposed, in order to reach a devices selection procedure for the FL framework able to optimize the problem formulated in (16)-(19), considering the case of a 6G network connectivity. Therefore, due to the high susceptibility of the 6G channels to the surrounding environment, the ESNs, available at each device site, are exploited to forecast the communication channel conditions, by considering as forecasting horizon the period of time expected to complete the FL process. Then, on the basis of predictions performed, and considering the maximization of the system utility given in (15) and exploited in (23), the devices selection is performed. Specifically, the devices selection is realized through the formulation of a matching game between the set of devices and $\mathcal{A}$. In fact, $\mathcal{A}$ selects the most preferred devices on the basis of (23) and updates the associated available resources (see step 6 of devices selection algorithm). Once the devices taking part in the FL process have been identified, the possibility to use D2D communications instead of direct communication is considered by each of them whenever on some slot bad direct channel conditions are foreseen by the local ESN with the main aim at avoiding energy waste in failure updating parameters transmissions and do not worsen the FL process convergence time.

[6]In the case of a multiple selection as D2D host by more than one device involved in the FL process the choice is random.

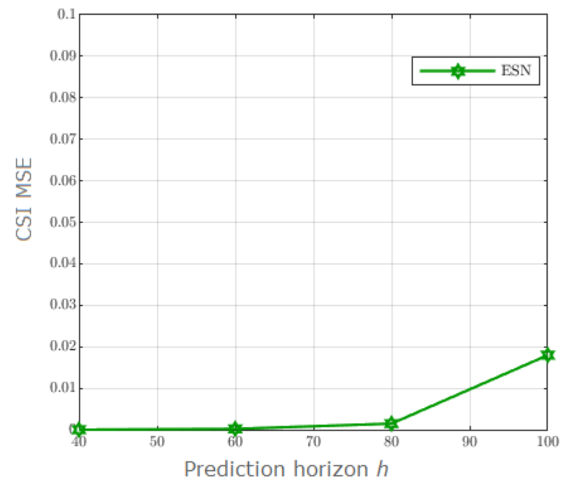


**FIGURE 5.** CSI MSE values as a function of the prediction horizon $h$, i.e., the time on which the prediction occurs.

## VI. PERFORMANCE ANALYSIS

In this section we evaluate the performance of the proposed solution by resorting to extensive computer simulations, and Tensorflow environment. In addition to this, performance comparisons with the vanilla version of the FL as baseline alternative, is also provided to highlight the advantages of the proposed approach. More specifically, in the considered vanilla FL scheme, devices selection follows a random-batch based policy [26]. Furthermore, any mechanism to incentive and select devices is not provided as well as the possibility to resort to the D2D mode. In order to accurately investigate the system behavior, we have considering different values for the number of devices, number of iterations, and time horizon $h$. Then, we have assumed $P = 600mW$, $P_D = 200$ mW,

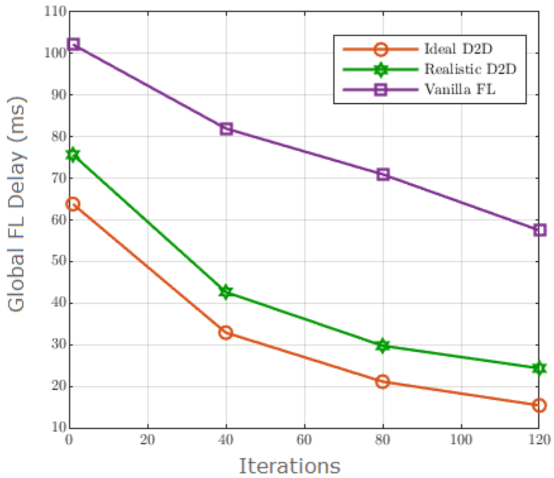


**FIGURE 6.** Global FL delay as a function of the number of iterations.

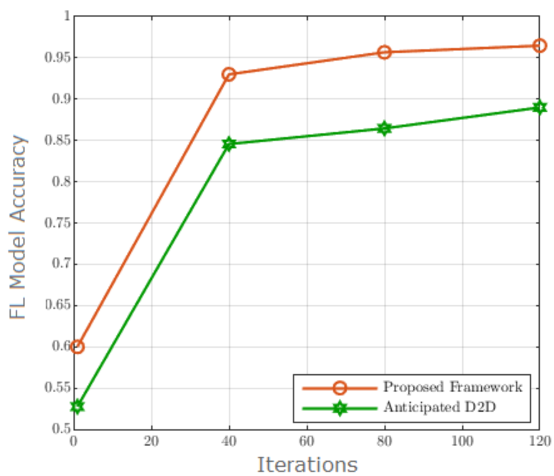


**FIGURE 7.** FL Model accuracy as a function of the number of iterations.

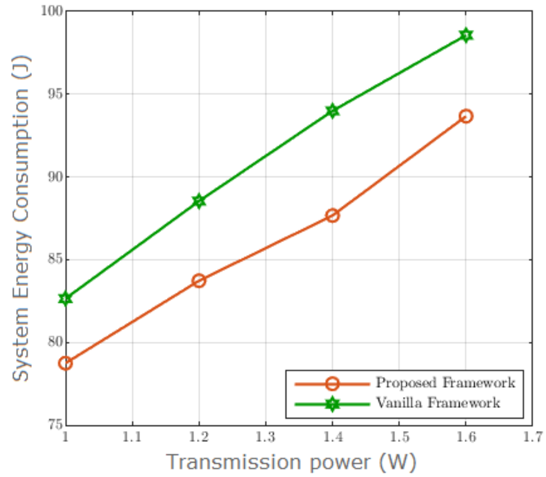


**FIGURE 8.** System energy consumption as a function of the transmission power.

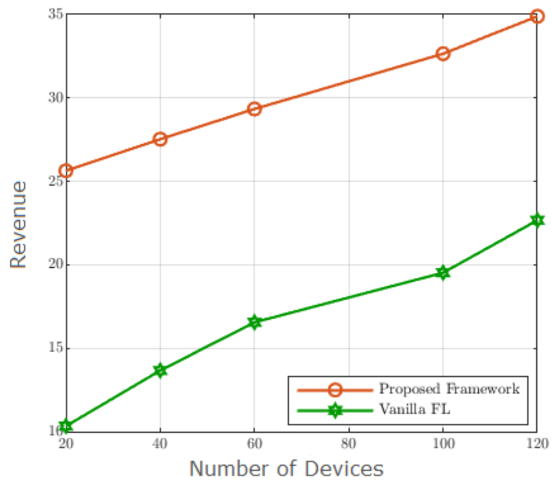


**FIGURE 9.** Revenue as a function of the number of devices.

$\mathcal{W} = 13$GHz, $K(\phi) = 0.0016m^{-1}$, vapor water percentage equal to 1%, a carrier frequency equal to 1 THz as in [4], while a range for discovering nearby devices equal to 3.86 m has been considered in order to allow D2D communications at the same rate of the direct link. Furthermore, $\epsilon_i = 0.1$, the size of the local model parameter $v_i$, has been set to 5 MB and equal for all the devices belonging to $\mathcal{M}$, whereas the amount of data for each device has been set as $D_i = 1000$ MB according to [19]. Likewise, as in [19], the CPU frequency has been randomly selected within the interval [10, 20] MHz. With the aim at testing the accuracy of the ESN used in the paper for the channel prediction, the mean squared error (MSE), given below, has been adopted as error measure

$$MSE = \frac{1}{|\mathcal{E}_{i,h}|}\sum_{\eta=1}^{|\mathcal{E}_{i,h}|}(\hat{\iota}_{\mathcal{E}_{i,h}} - \iota_{\mathcal{E}_{i,h}})^2 \tag{25}$$

In (25) $\hat{\iota}_{\mathcal{E}_{i,h}}$ and $\iota_{\mathcal{E}_{i,h}}$ are the predicted and the actual value, respectively. In addition, in order to test the ESN accuracy, we have resorted to actual 6G channel data measurements released by [32].

To this regards, Figure 5 shows the accuracy behavior of the CSI predictions provided by the considered ESN in terms of resulting MSE values, given by (25), as a function of the prediction time horizon $h$. As it can be easily to note in this figure, as the time horizon grows, the resulting MSE values get worse, i.e., the MSE values increase. This is an expected trend due to the intrinsic complexity of predicting long-term time series behavior. However, we highlight that the achieved MSE values remain relatively low, even when $h$ is high. Figure 6 shows the global convergence time of the proposed D2D-aided FL scheme as a function of the iterations number, by considering, as alternatives, the two D2D selection strategies outlined in Sec.V-B and assuming a number of selected FL devices equal to the overall number of devices. In the same Figure the convergence time of the considered vanilla version of the FL process is also reported for comparison purposes. As expected, the use of

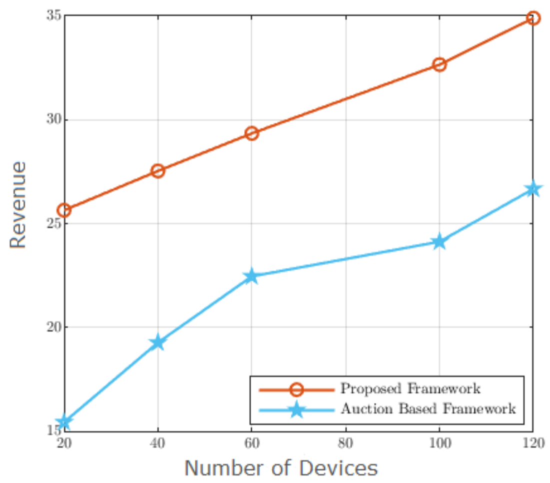


**FIGURE 10.** Revenue as a function of the number of devices.

the ideal D2D selection scheme in the proposed FL approach reaches better performance (upper bound) in comparison to the SBS-assisted D2D selection scheme alternative. However, it is important to stress that the performance achieved by the SBS-assisted D2D selection scheme are close to the upper bound, thus certifying it as an efficient viable solution for actual applications. Figure 6 validates the effectiveness of integrating an incentive mechanism to boost the FL performance in terms of global FL delay, i.e., the overall time spent to complete the model training. Likewise, Figure 7, shows that the FL model accuracy reaches higher values adopting the proposed framework, in comparison to the vanilla alternative. It is evident in this figure, that the FL model accuracy increases as the number of iterations grows. This is valid for both the considered schemes, under the assumption of same communications opportunity, due to the fact that in each of them the learning process takes advantage by an increased number of iterations. Note that the number of iterations represents the number of learning iterations required to reach a desired level of accuracy. Furthermore, at the benefit of the completeness of our analysis, Figure 8 illustrates the advantages of the proposed solution also in term of energy consumption. In particular, this Figure represents the system energy consumption as a function of the power level used in transmission by the FL selected devices to communicate with the aggregator. It straightforward to note in this Figure that, by increasing the power used in transmission, the energy consumption grows. Despite this, the advantages in terms of energy consumption of the proposed scheme in comparison to the vanilla alternative are clearly evident in Figure 8. The functional integration of a proper devices incentive mechanism in the proposed D2D-aided FL scheme is highlighted by the following Figures. Whit reference to this, Figure 9 depicts the revenue trend as a function of the number of devices. Again, the proposed framework clearly outperforms the vanilla scheme. In fact, the curves behavior highlight the effectiveness of both the incentive and the selection strategy to improve the federated learning performance. For the sake of completeness of our analysis, Figure 10 illustrates the revenue reached by the proposed framework in comparison with the scheme in which the vanilla FL is applied and an auction-based incentive mechanism as in [8] is used. Note that the incentive mechanism proposed in [8] has been properly modified to be adapted to the scenario considered in this paper. Specifically, we have bypassed the transmission power selection strategy that is out of the scope of this paper, and we have considered as auction bids the users utility. Then, in compliance with [8], we have applied the well-known Vickrey-Clarke-Groves market mechanism. As it is evident to note, the proposed framework outperforms the strategy presented in [8], confirming once again the validity of the scheme proposed. In conclusion, we can state that the presented results has clearly validate the proposed D2D-aided FL scheme as an efficient approach to enable an effective FL models integration in the new AI-empowered generation networks.

## VII. CONCLUSION

This paper has addressed the problem of devices selection with incentive in a D2D-aided FL scheme for applications in 6G based networks. Within this perspective, the paper demonstrates the advantages of a joint application of ML and MT approaches in a proper FL framework where users have the possibility to forecast the channel communication conditions towards the aggregator by mean of a local ESN. On the basis of the predictions about the channel state, whenever bad propagation conditions are detected, users can resort to the cooperation of a nearby device (if any) activating a D2D communication to send the local update to the aggregator. Simulation results have been provided to highlight the advantages of the proposed D2D-aided FL scheme with incentive mechanism in a 6G environment in comparison with a vanilla alternate in terms of a lower global FL delay and energy consumption.

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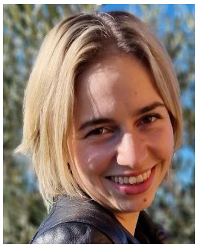

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