A Federated Learning and Blockchain-Enabled Sustainable Energy Trade at the Edge: A Framework for Industry 4.0

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***Abstract*—Through the digitization of essential functional processes, Industry 4.0 aims to build knowledgeable, networked, and stable value chains. Network trustworthiness is a critical component of network security that is built on positive interactions, guarantees, transparency, and accountability. Blockchain technology has drawn the attention of researchers in various fields of data science as a safe and low-cost platform to track a large number of eventual transactions. Such a technique is adaptable to the renewable energy-trade sector, which suffers from security and trustworthy issues. Having a decentralized energy infrastructure, that is supported by blockchain and artificial intelligence, enables smart and secure microgrid energy trading. The new age of industrial production will be highly versatile in terms of production volume and customization. As such a robust collaboration solution between consumers, businesses, and suppliers must be both secure and sustainable. In this article, we introduce a cooperative and distributed framework that relies on computing, communication, and intelligence capabilities of edge and end devices to enable secure energy trading, remote monitoring, and network trustworthiness. The blockchain and federated learning-enabled solution provide secure energy trading between different critical entities. Such a technique, coupled with 5G and beyond networks, would enable mass surveillance, monitoring, and analysis to occur at the edge. Performance evaluations are conducted to test the effectiveness of the proposed solution in terms of reliability and responsiveness in a vehicular network energy-trade scenario.**

***Index Terms*—Artificial intelligence (AI), blockchain, critical energy infrastructure, federated learning (FL), Industry 5.0.**

I. Introduction

With the growth in energy demands, and increasing pressure from consumers to reduce prices and develop services, markets are rapidly shifting toward green energy production. The energy industry is evolving; technologies have made the energy market more competitive, allowing businesses and households to invest in their energy production and storage facilities [1]. Today, solar and wind energy solutions have seen significant improvements. In essence, consumers are given more options than before in energy supply to meet their energy requirements. More facilities are now also linked and connected to provide the increased and supplemental power supply. The transition to green energy necessitates a better balance between centrally controlled and federated properties, which can then be integrated to develop potential power systems. To achieve this, the energy sector must adopt emerging technologies, such as blockchain, artificial intelligence (AI), and the Internet of Things (IoT). Using IoT ensures that all devices could be connected together and to the power grid. However, connected IoT devices introduce a network trustworthiness issue.

Wireless communication and next-generation technologies (e.g., AI and blockchain) both have contributed to substantial changes in all sectors (e.g., government and industry). Such technologies are now being adapted for a variety of energy-based applications. Beyond 5G (B5G) networks are now enabling on-demand services and wireless cellular charging in the energy sector [2]. As a result, these applications would produce massive amounts of data, enabling more in-depth learning and analysis. However, due to security and privacy issues, sharing and communicating the generated data requires extreme caution.

Energy prosumers (i.e., consumers and producers) must feel secure when involved in energy trading, given that highly confidential and private data may be disclosed. Energy-trade solutions must be able to take the advantage of AI and blockchain solutions to ensure data confidentiality and protection. Energy systems must consider effective and accurate storage, processing, and communication of the vast real-time data gathered from the edge and end devices in order to maintain an effective early-stage alert, problem avoidance, and control. Furthermore, systems that deal with critical data sharing and processing should comply with a variety of standards related to shared-data user privacy and security imposed by government authorities or individuals [3]. Given the advancements of today's smart edge and end devices, the majority of data training and learning could be processed in a fully decentralized or distributed manner.

The main contributions of the manuscript are as follows.

1) We develop a federated learning (FL)-supported framework for energy trade among prosumers, that adopts blockchain to safely and securely authenticate

Manuscript received 10 May 2021; revised 23 September 2021; accepted 29 November 2021. Date of publication 5 January 2022; date of current version 6 February 2023. This work was supported by the College of Technological Innovation (CTI), Zayed University (ZU), under Grant RIF-20130. *(Corresponding author: Safa Otoum.)*

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Digital Object Identifier 10.1109/JIOT.2022.3140430

transactions in a distributed and decentralized manner. The solution allows for prosumer resources to be advertised so that consumer energy requests are retrieved with minimal delays.

2) We solve a profit maximization problem using FL given consistent and up-to-date edge and end-device resource and capability advertisements using a clustering and lookup mechanism.
3) We ensure the authenticity and security of the participants by creating task composition plans and selecting the one that returns the maximum profit and then upload it on the blockchain.
4) Evaluations are conducted to test the latency and responsiveness of the clustering and communication mechanism against other distributed and centralized solutions.

The remainder of this article will discuss some background and literature review in Section II. The proposed solution is discussed in Section III. Simulation results are looked at in Section IV. Challenges are looked at in Section V. This article is finally concluded in Section VI.

II. Background and Related Work

A. Distributed and Decentralized Energy Models

Intelligent energy systems are heading toward distributed and decentralized models that accommodate heterogeneous and efficient energy generation and storage. Most of the currently running infrastructures are centralized and require the presence of third-party management and authentication. The centralized trading model has some limitations and becomes unappealing for energy suppliers. Decentralized solutions, on the other hand, can become an alternative for energy prosumers. A number of attempts have been made to provide decentralized and distributed energy trade. Brooklyn MicroGrid is a blockchain-based Peer-to-Peer (P2P) energy-trading solution that has been constructed in the Brooklyn neighborhoods of Gowanus and Park Slope [4]. It has completed a three-month trial period of energy trading. Brooklyn MicroGrid adopts Ethereum-supported smart contracts along with using the practical Byzantine fault-tolerance (pBFT) consensus method that enables consumers to sell their extra produced energy to neighbors. Green Energy Wallet is another example of adopting blockchain in the energy sector [5] that uses blockchain technology to make residential storage systems (e.g., home and electric vehicle batteries) available for rent.

In [6], a P2P energy-trading framework is presented that is supported by blockchain. It relies on the usage of bilateral smart contracts, an electronic-commerce platform, a double-auction algorithm, and the support of trading functionalities with the main grid. The double-auction technique which uses the Vickrey–Clarke–Groves (VCG) algorithm avoids any market power exercise. This is achieved through incentivized bidding of participants. The solution allows for various trading preferences and electricity generation attributes and consumption to be met. A consortium blockchain infrastructure is established, offering permission distributed ledger and energy trading.

B. AI-Assisted Energy Systems

AI and machine learning (ML) have been used for enhancing energy efficiency to support decentralized energy-trade models and support efficient energy usage [7], [8]. Jamil *et al.* [8] proposed a blockchain-assisted predictive energy-trading model that provides real-time assistance, control, as well as scheduling for distributed energy resources in order to meet the smart grid's demands. Their proposed model is made up of two components: 1) the blockchain energy-trading module for providing real-time energy monitoring and trading and 2) the smart contract predictive analytics for creating predictions based on past energy consumption.

In Verdigris Technologies, a cloud-based computing platform is developed that uses AI to help users reduce their energy consumption [9]. Different IoT devices such as sensors are connected to consumer electrical circuits to monitor their energy use. The collected data is securely sent to the cloud, allowing for online data access. Since each machine has its own electric characteristics, the AI algorithms were designed to differentiate between them while also providing a thorough analysis of the collected sensory data.

Another example of applying AI in the energy sector has been presented in [10]. Verv is a home assistance system powered by AI that offers energy statistics on home appliances and regularly itemizes energy costs. Consumers can monitor and regulate their appliances' energy consumption rates, as well as their energy costs. The AI-assisted mechanism keeps records of the energy costs that each item uses. It also includes safety features such as alerts when machines are left on for lengthy periods of time and carbon pollution reduction tips. In [9], PowerScout has developed an AI-assisted solution that models future utilities' cost savings. It assists clients to make purchasing choices for clean home energy technology.

C. FL-Supported Energy Systems

FL allows for the training of local models to create a global model with minimal support from centralized entities. It is a cooperative and secure solution, such that the trained data is locally accumulated and trained at the end devices. Such a learning solution is highly adaptable to the energy-trade model, where prosumers are connected to edge devices that collect locally shared data. The training is performed on the edge devices for faster, secure, and accurate prediction results. Although an abundance of ML solutions exists, FL with the support of Blockchain technology, secure data transmission and sharing could be preserved.

In [11], a federated energy demand learning solution is proposed to predict energy demands for electric vehicle networks. Charging stations perform FL on locally gathered information from serviced electric vehicles, then share the trained model with charging station providers. The communication overhead is significantly reduced, while users' data is protected and kept private. To improve the prediction accuracy, a clustering learning-based solution is used to classify the charging stations before performing the learning to reduce the dimensionality of the data set and minimize biased predictions. Evaluations reveal that communication overhead is reduced

TABLE I
COMPARING FL AND DISTRIBUTED LEARNING IN TERMS OF THEIR ADVANTAGES AND DISADVANTAGES WHEN ADAPTED TO CRITICAL INFRASTRUCTURES LIKE ENERGY SYSTEMS

	Distributed Learning	Federated Learning
Data Distribution	- Centralized storage of consumers' data. - Data is accessible by consumers only.	- Consumers' data is generated locally. - Decentralized storage of consumers' data. - Each customer preserves its own data. - Consumers do not have access to data stored at other consumers.
Model Setting	- Training the model on a large consumer data-set. - Consumers are nodes in a cluster or data center.	- Training is conducted locally on consumers devices.
Data Availability	- All consumers are assumed to be available.	- All consumers might be available. - A fraction of consumers are available at any point of time in certain FL scenarios.
Main Drawback	- Computation is processed at the data-center.	- Diversified end-device capabilities may cause issues with computation and communication.
Addressability	- Each customer has its own identity that allows the system to reach it.	- Each customer has its own identity or name that allows the system to reach it.
Customers' Reliability	- Few failures.	- Few to moderate levels of failures, depending on device capabilities.
Wide-area communication	- No wide-area Communication. - Consumers are grouped into one cluster.	- A coordinating service provider is required along with consistent connection with consumers.

by 83.4%, while enhancing prediction accuracy by $\approx 25\%$. Table I outlines the advantages and disadvantages of applying FL to energy management systems in comparison to distributed learning approaches.

D. Blockchain-Enabled Energy Trade

P2P energy sharing will help keep the power grid running smoothly. Blockchain is a distributed/decentralized ledger system that has the potential to improve energy exchange by making it simpler, cheaper, and more transparent [12]. It allows prosumers to buy and sell energy directly with one another without the use of intermediaries. Blockchain has been used for enhancing energy solutions. Many researchers have examined the use of blockchain technology in energy-related applications [13], [14]. Trading trustworthiness is considered a very crucial element in achieving energy security. Energy collection and sharing between distributed peers can be extremely sensitive in distributed and decentralized systems. As a consequence, in a distributed energy-trading system where energy is collected from customers and shared through neighbors, a secure and confidential trading mechanism would be required. Furthermore, in a collaborative energy-trading environment where localized and centralized peers may need real-time access to energy, privacy-preserving structures that provide proper system integration of entities are necessary. Access to services, consumer identity monitoring, and energy disclosure are all necessary features of any cutting-edge distributed and intelligent energy-trading system.

For such cooperative and collaborative systems, where the energy system would be made up of a large number of organizations and users in sparse locations, blockchain is important. It offers a distributed and decentralized method for securely sharing and storing confidential data. Energy prosumers will be able to interact and share a unique paradigm across multiple sectors. Since most participants must validate each block of data, the adopted blockchain consensus algorithm would render it virtually hard to change transaction records, this would effectively eliminate cyber-attacks on energy storage sites.

The blockchain elements that make it applicable to energy-trading scenarios are: 1) smart contracts used between participants of the energy-trade model; 2) applicability in both public and private energy-trade scenarios; 3) consensus mechanism which enables verification for every transaction, where no changes can be done on the records; and 4) the digital ledger which is responsible for verifying the transactions. We rely on both public and private blockchains. For instance, if a particular energy-trade process relies on nodes within the same service network, then a private blockchain is deployed. On the contrary, when the composition process involves multiple clusters from different serviced networks, then a public blockchain is deployed.

III. PROPOSED SOLUTION

A number of differences exist between the presented solution and other earlier works in the literature, such as in [14]. Most earlier works assume that the requested energy is provided by one prosumer, whereas in our work, the request might be fulfilled by multiple energy prosumers depending on the specifics of the request in terms of energy, QoS, and other service requirements. A composition solution is adapted to ensure that a number of composition plans are created, and the one with the highest probability of attaining the maximum shared profit from the set of plans is selected upon resource lookup. Second, we adopt a clustering algorithm that groups similar services/capabilities of devices for faster solution lookup, with the support of FL. Such a solution would decompose the service requests into different tasks that may be achievable by a group of prosumers for a maximized profit, in addition to accurate and efficient service delivery. Whereas in other works, a centralized learning approach is adopted to support the energy selection process. Fig. 1 depicts a high-level overview of the proposed blockchain-enabled FL-supported energy-trade architecture. Table II defines some of the most used notations in this article.

A. Profit Maximization Model

We assume a cooperative network environment composed of M users that are willing to cooperate and trade energy in return for money or other resources/service incentives. We assume that all participating devices have processing, communication,

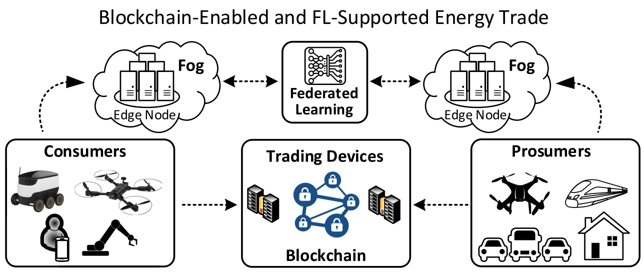

Fig. 1. High-level overview of the blockchain-enabled and FL-supported energy-trade model. The solution integrates intelligent devices, blockchain technology, and FL with next-generation networking for Industry 4.0.

TABLE II
DESCRIPTION OF SOME OF THE MOST USED NOTATIONS IN THIS ARTICLE

Notation	Notation Description
E_{req}	Energy request
cap_m	Participant capabilities
$E_{req}^{Description}$	The amount of energy requested/provided
E_{req}^{QoS}	The acceptable QoS parameters defined by the requester.
RW_q	Reward
$\grave{q}_{E_{req}}$	Successful energy resource or capability provided by the device at time t, $\underline{q}_{E_{req}} \leq \grave{q}_{E_{req}}(t) \leq \overline{q}_{E_{req}}$
PN_q	Penalty
$\cap$	The set of resources and capabilities found in device m and $m+1$
$\cup$	The set of resources and capabilities that are either not found in device m but found in device $m+1$
$\omega_\cap$ and $\omega_\cup$	The weights for each set of found and not found resources/capabilities
C_t	A random set of users, where $(\lvert C_t\rvert = \mathbb{C}.u \geq 1)$
m_t	Master model
$\mathbb{C}$	The users' fraction
$\mathbb{I}$	The local epochs number
α_{prop}	The area for the proposed system
α_{ideal}	The area for the ideal system
S_{def}	The score of default entities
S_{n-def}	The score of non-default entities

and energy storage capabilities used for the collaborative smart energy-trading task. With that said, an end or edge device may request service in the form of energy request E_{req}, which can be fulfilled by one or more participant capabilities cap_m. In essence, combining participant capabilities $\text{cap}_m \cup \text{cap}_{m+1}$ in a composite fashion will fulfill E_{req}. For instance, a node requesting a specific amount of energy may be fulfilled by having more than one participating device to process the requested task. Moreover, an energy transaction may require temporary storage of energy at a third-party node to fulfill the transaction. As a result, that third-party participant will be rewarded for its participation. The selection of the candidate participating devices in the cooperative energy-trade process is fulfilled according to the requester's and participants' preferences and current network and resource availabilities.

Devices communicate their request to the nearest participant in the network, in accordance with the requested preferences and service qualities, such that $E_{\text{req}} = \{E_{\text{req}}^{\text{Description}}, E_{\text{req}}^{\text{QoS}}\}$. $E_{\text{req}}^{\text{Description}}$ is defined by the amount of energy requested/provided, the duration for the request, and services that may need to be provided, such as temporary storage and other communication services. $E_{\text{req}}^{\text{QoS}}$ is defined as the acceptable QoS parameters defined by the requester and can be incorporated as the Class of Service (CoS) for a particular service type. We assume that the requested service may be decomposed into a set of tasks that can be offered by participants. For instance, a device may have intelligence capabilities to predict the amount of power usage that a requester may need for a certain duration. Such a task can be considered as part of a service request and is hence advertised as part of the device's capabilities.

We assume that the process of service request, advertisement, composition, and delivery is achieved in a distributed and decentralized fashion. As such, resource/capability pooling and lookup must be conducted in a distributed and secure manner. Participating nodes thus create resource/capability clusters based on the advertised participant resource/capability descriptions. Given that resource/capabilities are advertised, and through the proposed clustering method, changes to the available resources are reflected by the updated resource pools. Due to the dynamic nature of the network environment, the resource management process is achieved cooperatively between the service nodes. In essence, resource delivery is achieved either directly by performing request matching, or through a composition process that requires the cooperation and the composition of the service $E_{\text{req}} = \text{cap}_m \cup \text{cap}_{m+1} \Leftrightarrow \text{cap}_m, \text{cap}_{m+1} \in S$. The cooperative process must ensure that the overall shared profit of the cooperative devices is maximized while adhering to the resource and device capability constraints, as defined in (1) and (2).

To achieve a maximized profit $P_{E_{\text{req}}}$ at time t, for each participating device m from the set $m = \{1, 2, \ldots, M\}$, the provided accumulated energy resource or capability $\grave{q}_{E_{\text{req}}}$ at time t needs to maintain the highest reward value RW_q. This is achieved by ensuring that the provided resource is within the acceptable limits set by the service request, namely, $\underline{q}_{E_{\text{req}}} \leq \grave{q}_{E_{\text{req}}}(t) \leq \overline{q}_{E_{\text{req}}}$, such that $\underline{q}_{E_{\text{req}}}$ is the minimum acceptable resource or service quality, and $\overline{q}_{E_{\text{req}}}$ is the maximum needed resource quality. Moreover, when selecting the resource, the workload incurred on a device $WL_{E_{\text{req}}}$ for request E_{req} at time t as a result of the participation in terms of processing, communication, storage, and power usage must also be taken into account. Furthermore, penalties incurred as a result of fulfilling a request PN_q is also considered as part of the profit calculation

$$\begin{aligned} \text{maximize} \quad & \sum_{m=1}^{M} P_{E_{\text{req}}}(t) \\ \text{s.t.} \quad & \left(\sum_{n=1}^{N} r_n(t)\right) \leq R(t) \end{aligned} \tag{1}$$

$$\begin{aligned} P_{E_{\text{req}}}(t) = & \left(\sum_{m=1}^{M} RW_q \times \grave{q}_{E_{\text{req}}}(t)\right) \\ & - \left(\sum_{m=1}^{M} WL_{E_{\text{req}}}(t) + \sum_{m=1}^{M} PN_q \times \grave{q}_{E_{\text{req}}}(t)\right). \end{aligned} \tag{2}$$

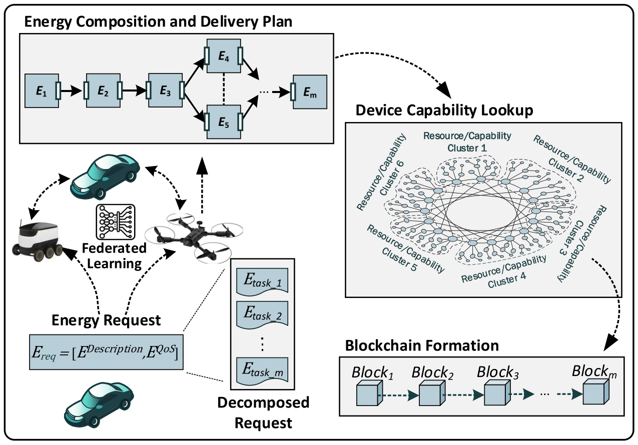

Fig. 2. Decentralized cooperative energy-trade solution that relies on resource and device capabilities, in addition to FL and blockchain for Industry 4.0.

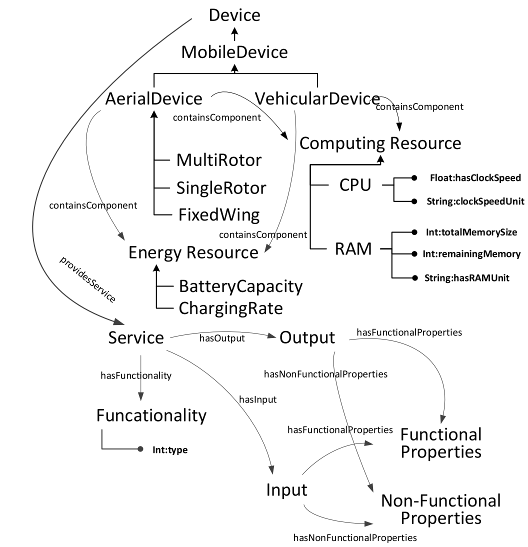

Fig. 3. Illustration of the part of an ontology that models device capabilities and resources. As an example, an aerial device is considered a device that has computing resources and energy resources and provides services described through input and output properties.

B. FL-Based Composite Energy Trade

The adopted solution considers a decentralized approach toward energy trade using edge and end devices. Clusters are formed to group similar resource and device capabilities for faster search and retrieval. The process begins by decomposing the request into a set of tasks as shown in Fig. 2. A composition and delivery plan is developed with the aid of an FL approach that is integrated into participating end devices. Then, a resource and capability lookup is initiated on the formed resource/capability clusters. Finally, to authenticate the transaction, a blockchain is formed that incorporates all device capabilities and resources. The newly formed blockchain is then used for future requests as part of the learning process to speed up the delivery of new energy-trade requests.

1) Cluster Formation: Device capabilities and resources are clustered in accordance with a similarity function. The process begins by having each participant device advertise its available resources and capabilities to the nearest edge node. Capabilities having similar descriptions and characteristics according to (3), in terms of closeness (i.e., semantic distance) form a cluster together. The resources and capabilities of devices are described using an ontology as depicted in Fig. 3. As such, the similarity function in (3) is used to determine the closeness of two device descriptions

$$\frac{|\mathrm{cap}_m \cap \mathrm{cap}_{m+1}|}{\omega_{\cap}|\mathrm{cap}_m \cap \mathrm{cap}_{m+1}| + \omega_{\cup}|\mathrm{cap}_m \cup \mathrm{cap}_{m+1}|} \tag{3}$$

where $\cap$ defines the set of resources and capabilities found in device m and $m+1$. $\cup$ defines the set of resources and capabilities that are either not found in device m but found in device $m+1$, or vice versa. $\omega_{\cap}$ and $\omega_{\cup}$ define the weights for each set of found and not found resources/capabilities, respectively.

A device from each cluster is selected to act as a discovery node for devices of other clusters. As such, device resources and capabilities are discoverable in a decentralized fashion. The selection process of discovery nodes in clusters is based on the device's power and stability descriptions [15]. A device that has more residual power, low communication, and power consumption and has been present in the environment for longer periods is selected as a discovery node. Discovery nodes are incentivized for the discovery service they provide [16] and are supported by edge nodes (e.g., multiaccess edge nodes [17]) when adapting FL for the composition process. As such, cooperation among discovery and edge nodes will provide a larger set of discoverable clusters. In essence, this will lead to faster resource discovery and delivery.

2) Resource Composition and Energy Delivery Plan: Upon submission of an energy request from an end device, composition and delivery plans are formed. A plan would represent a workflow of the set devices that can participate, by providing some of their resources and capabilities to achieve the set of tasks needed in order to optimally deliver the energy request. The plan is modeled as a set of tasks associated with devices, having input conditions prior to performing the tasks and output results after performing the task. As discussed earlier, such tasks may involve not only energy resources but also communication, processing, and intermediate storage. Some tasks can be performed in parallel, while others are performed in sequence (see composition and delivery plan outline in Fig. 2). The composition plan is supported with an FL algorithm (discussed later), that determines the optimal device selection strategy by solving the problem outlined in (1). Once the plan is formed, it is then forwarded to the nearest edge device (i.e., MEC node), which in essence will communicate the composition request to the discovery nodes of the clusters. Given that discovery nodes are able to discover services from other clusters (with the support of discovery nodes from the other clusters), it is thus assumed that all resources and capabilities are discoverable, in essence leading to an optimal composition plan. Algorithm 1 summarizes the resource/capability discovery and composition process.

3) FL-Supported Composition Plan: Using FL in critical infrastructures enables user data privacy, where user data are not shared with others, in essence leading to an optimal degree

Algorithm 1 Resource Discovery and Composition Procedure

for each request E_{req} **do**
  Decompose E_{req} into a set of tasks $\{E_{task_i}, E_{task_{i+1}}, ..., E_{task_I}\}$;
  Form a set of composition plans $\{Plan_j, Plan_{j+1}, ..., Plan_J\}$;
  Calculate probability of attaining maximum profit $P(P_{E_{req}}(t))$ from the set of plans according to (2) using FL;
  Perform resource lookup from the clusters to select $Max(similarity)$ according to (3);
Apply selected plan on the blockchain;

Algorithm 2 FL Procedure

procedure FEDERATED LEARNING(Server side)
m_0 : Server initialized model
  for each iteration $\mathbb{I}$ **do**
Perform $|C_t| = \mathbb{C}.u \geq 1$
    for each user $u \in |C_t|$ **do**
Update the user m^u_{t+1}
$$m_{t+1} = \sum_{u \in \mathbb{C}_{\approx}} \frac{n_u}{n_\alpha} m^u_{t+1}$$
procedure FEDERATED LEARNING(User side)
Receive m_t from the server
Initialize $m^u_{t,0} = m_t$
  for h= 0,1,2,... **do**
Select a sample β from D_{in} ▷ D_{in} = user dataset
Update $m^u_{t,h+1}$= $m^u_{t,h}$- ($m^u_{t,h}$, β)
  Set $m^u_{t+1} = m^u_{t,H_t}$
Send m^u_{t+1} back to the server

of data protection. Algorithm 2 represents the adopted FL technique. The algorithm considers all participants (i.e., end users and the server). In this work, we have adopted the stochastic gradient descent (SGD) for the training. Federated averaging starts by initializing the master model (at the server side) as m_0. Then, the server initiates the first round of averaging by selecting a random set of users (C_t, such as $|C_t| = \mathbb{C}.u \geq 1$) and applies its recent master model m_t to it (C_t). On the users' side, users consider the shared model from the server (m_t) by replacing their local models (m^u_t) with it. Each user then splits its data into subsets (of size $\mathbb{B}$) and performs $\mathbb{I}$ times of SGD, where $\mathbb{I}$ refers to the user data iteration number ahead of updating the master model. All users then upload their newly trained models (m^u_{t+1}) to the server, which constructs the newly updated master model m_{t+1} by performing a sum of all the collected models.

IV. Performance Evaluation

Evaluations were conducted to test the cooperative FL and blockchain-enabled energy-trade procedure in a vehicular network environment. We specifically focused on the communication overhead introduced, latency for service retrieval, request completion time, and the power overhead introduced on end devices using the decentralized solution. We considered a traffic data set retrieved from [18], used for vehicular node power consumption-related tests at different traffic stations. The data set captures data for an entire year from different cities across the United States. For the purpose of the evaluation, three traffic stations were only considered. The features used for the prediction are station ID, time, day of the week, day of the month, and direction of travel.

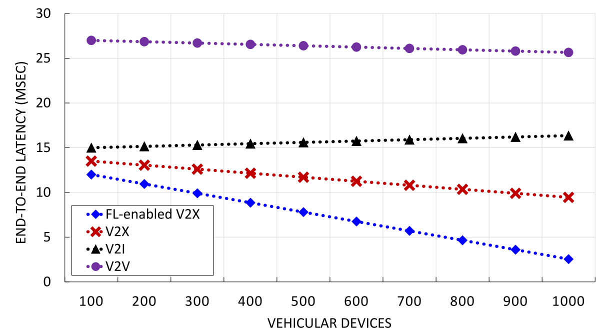

Fig. 4. End-to-end latency comparison of different resource discovery mechanisms for the composition and delivery of requested resources.

Simulations were performed using OMNET++ and the OverSim model to establish the decentralized communication network. The network topology was set up to accommodate for up to 1000 nodes in a 2000 × 2000-m 2-D overlay space. Node arrival and departure in the network were modeled using a lifetime-based churn model of exponential distribution with a fully recursive KBR protocol used to model the network traffic. Nodes were randomly distributed in the simulation environment. Device resource and capability descriptions were specified using OWL/RDF ontology files. Capability comparisons were conducted using OntoCAT.

The proposed cooperative solution (FL-enabled V2X) that relies on FL and blockchain to construct end-to-end composition paths for service delivery according to resource availability and user requirements, is compared against solutions with some limitations, namely, resource sharing among vehicular devices only (V2V), resource sharing with that of the infrastructure only (V2I), and resource sharing among cooperative devices and the infrastructure but without the use of FL and blockchain (V2X). Evaluations focused on the reliability and responsiveness of the proposed FL-enabled V2X solution. Results have shown that the solution enhances the reliability of the network by maintaining a high delivery rate and minimal device power consumption. Moreover, the optimal placement of unmanned aerial vehicles (UAVs) for nearby energy resource availability is realized through the support of FL. Given that the learning process is decentralized, the learning part is assumed to be run on edge devices in which the vehicular nodes are connected for communication and data retrieval.

Fig. 4 depicts the end-to-end latency accumulated as a result of the resource discovery and delivery confirmation process. Results show that a significant decrease in the end-to-end latency is experienced with the proposed solution in comparison to conventional communication mechanisms. With a network environment composed of 1000 vehicular nodes, the end-to-end latency reduction for FL-enabled V2X compared to that of V2V, V2I, and V2X is $\approx$ 23, $\approx$ 24, and $\approx$ 7 ms, respectively. This significant decrease in latency is a result of the learning performed from previous compositions and the availability of resources with the increased number of devices.

Fig. 5 depicts the packet delivery success rate achieved as a result of the decentralized resource discovery and selection mechanism (FL-enabled V2X) in comparison to the other schemes, namely, V2V, V2I, and V2X. Given that the proposed solution places devices, namely, UAVs, in locations

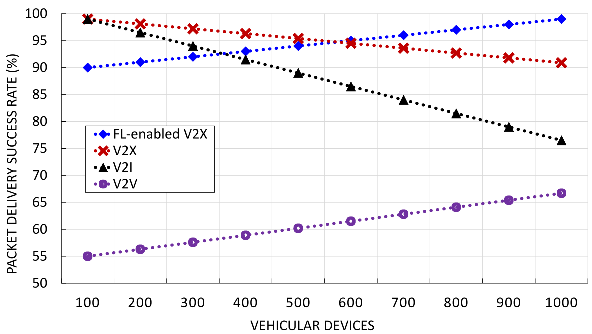

Fig. 5. Packet delivery comparison of resource discovery and delivery requests.

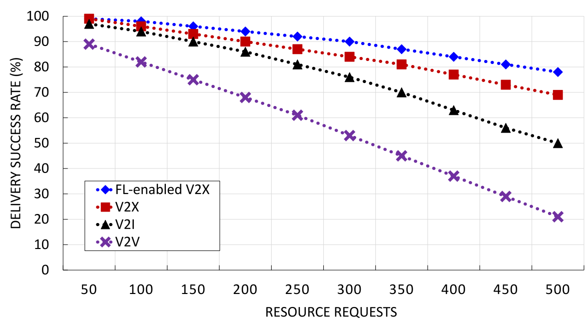

Fig. 6. Resource delivery success rate comparison as the number of resource requests grows.

that allow for faster communication and resource discovery, the packet delivery success rate increases significantly from $\approx 90\%$ to $\approx 99\%$ when 1000 vehicular nodes are available in the simulation environment. The high success rate will ensure that all resources are discoverable and deliverable.

Fig. 6 depicts the delivery success rate for requested resources. Results show that as the number of requests increases, the success rate decreases for all the mechanisms. This is due to having most of the device and infrastructure resources and capabilities already being used to fulfill other requests. But when comparing the FL-enabled V2X against the other solutions, we observe that the success rate does not drop sharply. As the number of requests increases from 50 to 500, we observe that the success rate drops by $\approx 20\%$ for the FL-enabled V2X solution. On the contrary, for the V2X, V2I, and V2V, the success rate drops by $\approx 30\%$, $\approx 47\%$, and $\approx 68\%$, respectively.

Fig. 7 depicts the accumulated profit for all participating devices (i.e., end devices, edge devices, and infrastructure resource providers). Results show that FL-enabled V2X accumulates the maximum shared profit in comparison to the other solutions. This is due to having the FL mechanism determine the most optimal composition path and resource selection to ensure maximized profit for all participants. In comparison to V2X, the FL-enabled V2X solution provides an increased profit of ≈ 45 profit units in a simulation scenario of 1000 vehicular devices.

The energy load over devices has been represented in Fig. 8. When compared to the other scenarios, it is clear that the FL-enabled V2X has enhanced the system by lowering the load over devices. Fig. 9 shows how long it takes to submit

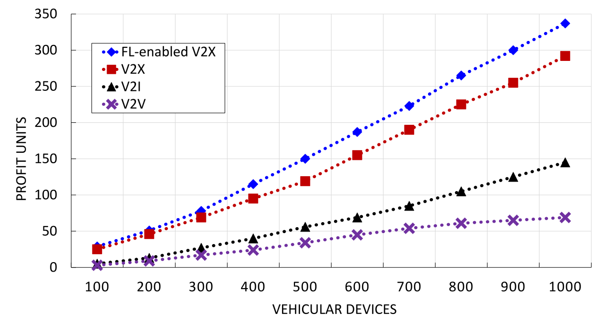

Fig. 7. Accumulated profit for all participants for participating in the resource delivery task.

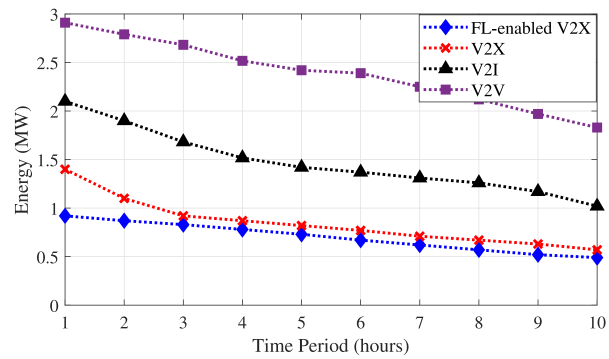

Fig. 8. Energy load over devices.

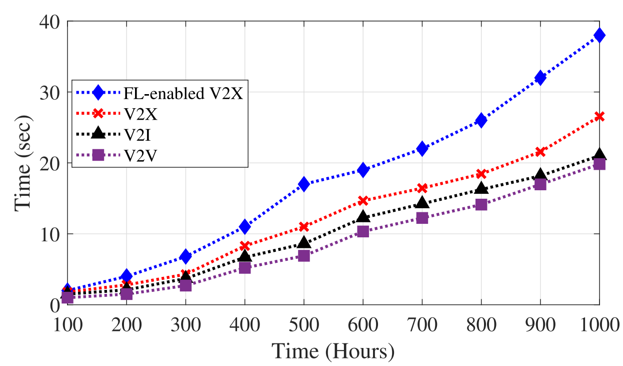

Fig. 9. Request completion time with various number of requests.

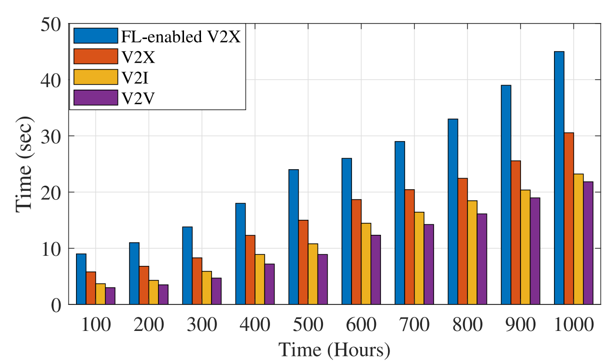

Fig. 10. Request completion time with various number of prosumers.

various amounts of energy requests. FL-enabled V2X has been compared against the other scenarios (i.e., V2X, V2I, and V2V). With an increase in the number of energy requests, the time it takes to complete the request increases. Fig. 10 shows

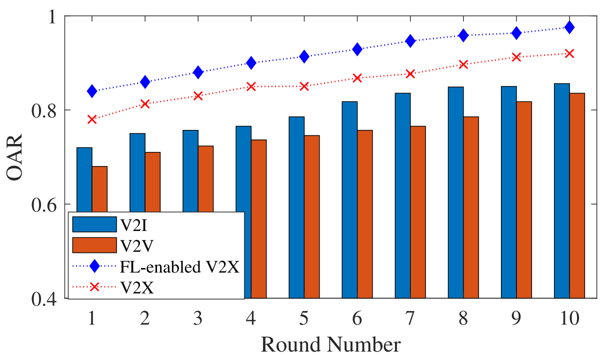

Fig. 11. OAR comparison with various round numbers between the different scenarios.

another comparison of time requests with different numbers of prosumers. It is obvious that as the number of prosumers grows, the system's search space grows as well, affecting the request completion time.

The operational accuracy rate (OAR) is a summary empirical measure of the operational sensitivity and specificity. The OAR compares the cumulative accuracy profile (CAP) of the tested model to the ideal discriminating model. OAR is presented in (4) [19], where α_{prop} and α_{ideal} represent the areas for the proposed system and the ideal system, respectively. With considering the probabilities, OAR is represented as shown in (5) [19], where S_{def} and $S_{n-\text{def}}$ refer to the score of default and nondefault entities, respectively

$$\text{AR} = \frac{\alpha_{\text{prop}}}{\alpha_{\text{ideal}}} = \frac{2\int_0^1 \text{CAP}(u)du}{1-p} \tag{4}$$

$$\text{AR} = P\big[S_{\text{def}} < S_{n-\text{def}}\big] - P\big[S_{\text{def}} > S_{n-\text{def}}\big]. \tag{5}$$

Fig. 11 shows the comparison of FL-enabled V2X operational OAR against the other scenarios. It is obvious that the proposed FR-enabled V2X outperforms the other scenarios.

V. Challenges of Blockchain and FL Energy-Trade Systems

Blockchain is a revolutionary technology in the energy field that can be used for a number of purposes. However, the technology's true long-term value has yet to be demonstrated, owing to the fact that most schemes have only been tested in limited, early-stage ventures. As a result, several questions must be answered before blockchains can be widely applied in the energy sector [20].

1) *Scalability:* No system can currently achieve all desirable characteristics without significant tradeoffs when it comes to the consensus processes (e.g., energy requirements).
2) *Security:* The development of new algorithms is critical for blockchain systems. Bitcoin has shown to be highly vulnerable to cyber-attacks. External systems, such as smart contracts, are often the source of cyber-security vulnerabilities. The ability to withstand such attacks is important, particularly for critical infrastructure applications such as energy systems.
3) *High Development Cost:* While blockchain can save money by eliminating third parties, it does not have a competitive advantage over other systems and solutions on the market in some cases. Energy-trading transactions, for example, can be held in conventional databases. Furthermore, blockchain could necessitate the installation of costly new infrastructure (e.g., equipment, software, etc.). Smart meters are currently installed without computing capabilities, so integrating conventional smart meters and grid networks into distributed ledger technology could be expensive.
4) *Lack of Flexibility and Standardization:* Once a blockchain system is up and running, any changes to the governing protocols or code must be approved by the network devices. Such scenarios in the energy sector can cause consumer mistrust and uncertainty [21].

Furthermore, the adoption of FL into the energy sector may also have some drawbacks as follows.

1) *Robustness Against Failures:* In addition to the typical vulnerabilities that can target any ML technique, such as intrusion attacks and malicious end users, the distributed nature of FL, combined with its data constraints, opens the door to a variety of failures and attacks. Deciding the fault-tolerance strategies that can identify and fix certain deficiencies along with choosing the security procedures is considered a difficult task that must be undertaken in order to reach a satisfactory degree of robustness. Implementing and integrating secure communication at the end users and within the device-to-device communication could be the solution for the aforementioned drawback.
2) *Effectiveness Improvement:* The effectiveness of FL in energy systems can be improved through a variety of methods, including adapting various approaches to various users, considering better optimization algorithms, and enhancing communication capacity. The goal of FL is to develop a master/global model that avoids the risks in the training data collection, which is a federation of data from all users. The requirement to address certain characteristics, such as data availability, data delivery, addressability settings, user efficiency, and wide-area communication, distinguishes federated algorithms from distributed training methods.

VI. Conclusion

Industry 4.0 is capable of turning existing manufacturing operations into "smart factories" in order to boost efficiency, protection, and cost savings. Undoubtedly, the future of the energy sector will consider many of today's flaws and attempts to ensure proper control, prevention, and management. The decentralization and distribution of current energy systems and the adaptation of intelligent learning techniques will with no doubt be one of the development strategies that will be adopted today. The use of blockchain will be a critical part of all of today's smart solutions. The property of service selection that integrates customers' device capabilities, such as the hardware/software specifications, intelligent learning, and communication, will certainly help in tackling energy management issues. The aggregation of FL learned models at edge devices using various device and learning capabilities, will enable energy services to be performed in a distributed and autonomous manner without the involvement of third parties.

In this article, we presented a blockchain and FL-enabled energy-trade framework that allows end-user devices to share their energy resources and capabilities in the network environment. Energy resource requests are decomposed into a number of resource tasks, which are matched against the advertised device capabilities. A request composition plan is created with the support of FL to select the optimal choice of resources according to a profit maximization problem. Composed workflows are added to the blockchain to authenticate the transaction process. Simulations were conducted to test the framework's composition process. End-to-end latency and successful delivery rates of the system have shown its superiority over other centralized and decentralized solutions.

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