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# DECENTRALIZED FEDERATED LEARNING FOR IOT IN RENEWABLE ENERGY SYSTEMS

**Jayalekshmi M.B[1], Suvarnamukhi[2], Dr. P. Gomathi[3], G. Senthilkumar[4]**

[1]Assistant professor, Department of IT, Noorul Islam Centre for Higher Education, Kumaracoil-629 180, Thuckalay, Kanyakumari District, mbjaya2k5@gmail.com

[2]Department of CSE, Sreyas Institute of Engineering and Technology. Hyderabad, mukhi.suvarna@gmail.com

[3]Professor in Electronics and Communication Engineering, Study World College of Engineering, Coimbatore, p.gomathi2006@gmail.com

[4]Department of Computer Science and Engineering, Panimalar Engineering College, Chennai, India, senthilkumarprofessor@gmail.com

## Abstract

The Internet of Things includes a broad array of connected devices which continuously produce and exchange vast volumes of data. The integration of IoT sensor networks into renewable energy platforms—including smart grids, solar farms, and wind turbines—has empowered real-time, data-centric approaches to enhancing efficiency in energy generation, management, and usage. However, traditional methods of machine learning which rely on central data collection are often impractical in real-world IoT scenarios due to constraints such as limited energy resources and the mobility of devices. Federated Learning (FL) provides a viable option to these challenges by enabling model training across distributed devices without the requirement to transmit raw data. In this study, we introduce a novel energy-saving, distributed federated learning structure designed to minimize power consumption while maintaining performance across IoT networks.Experimental results show that the DFL framework provides strong and competitive predictive performance while at the same time significantly reducing communication costs and improved system resilience. This work provides a scalable and conscious solution for intelligent energy systems that have comprehensive benefits for the future of distributed energy management.

**Keywords-**Federated Learning, Decentralized Federated Learning, Internet of Things

## Introduction

Internet of Thingsrapidly gains traction. Thus, the Scenario analysis indicates that approximately 126 billion intelligent devices within the terrace will become terraces by 2030. As ubiquitous integration of IoT in a variety of implementation has become so important, achieving the Sustainable Development Goals is not active without IoT, especially when reducing energy consumption. The result is a huge amount of



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generated data and exchanged across those networks, including robotics, sensors, intelligent devices, and cell phones. This considerable amount of data must be analysed and refined to deliver the targetedplatform. The introduction of renewable energy accelerates as traditional fuel sources are exhausted faster. Energy is suitable for people, and planets are green resources. Energy from natural sources that supply or renew themselves without exhausting the planet's resources is renewable energy. Those green resales are like sunlight, shaft, wind, flood, rain, and more. Renewable energy can be determined to be virtually inexhaustible.

Low energy prices for renewables are affordable. More investments will be spent on materials and processing to build and maintain the facility. Renewable energy is often invested in the same continent in the same country or usually in the same city itself, creating work to promote local people economy.

Renewable energy has the lowest cost of generating electricity and can also be used to expand. Possibility to expand energy access by all regions: cities, suburbs and cities. All accessible signs are accessible green resources, which are great signs of improvement. It's safe and greatvalue.

Renewable energy providers have been experiencing globalized economic growth in recent years. This scaling requires you to maintain profitability and productive capacity. The report confirms that the proportion of renewable energy is expected to be applied at approximately 21.6% of the global performance mix. Using IoT for renewable energy can save electricity. IoT finds ways to optimize capacity for your expansion grid at remote locations. Focusing on the foreground of green source gives businesses a great deal.

Over the past decade, dramatic changes have been taking place in the energy sector as future renewable energy and thorough resource fatigue have been favoured. According to the International Energy Agency, renewable energy sources and the IoT economy will achieve a 43% profit in 2030. IoT plays a significant role in the developing power sector. It is difficult to imagine a future of unfathomable resources absence of IoT. So, let's see at the alternatives of how the reversible energy sector integrated IoT responds to power growth and how efficiency can improve.

In monitoring and controlling of the sources of renewable energy, the stack involved in the layers of perception or most levels below, network layers, middle levels, application layers, or top level. The stack responsible for collecting data is the perceptual segment. Gathers thorough detailsabout physical features that monitor and manage your surroundings. The level is equipped with a variety of sensor devices or other components to meet the configuration to meet the user's requirements.



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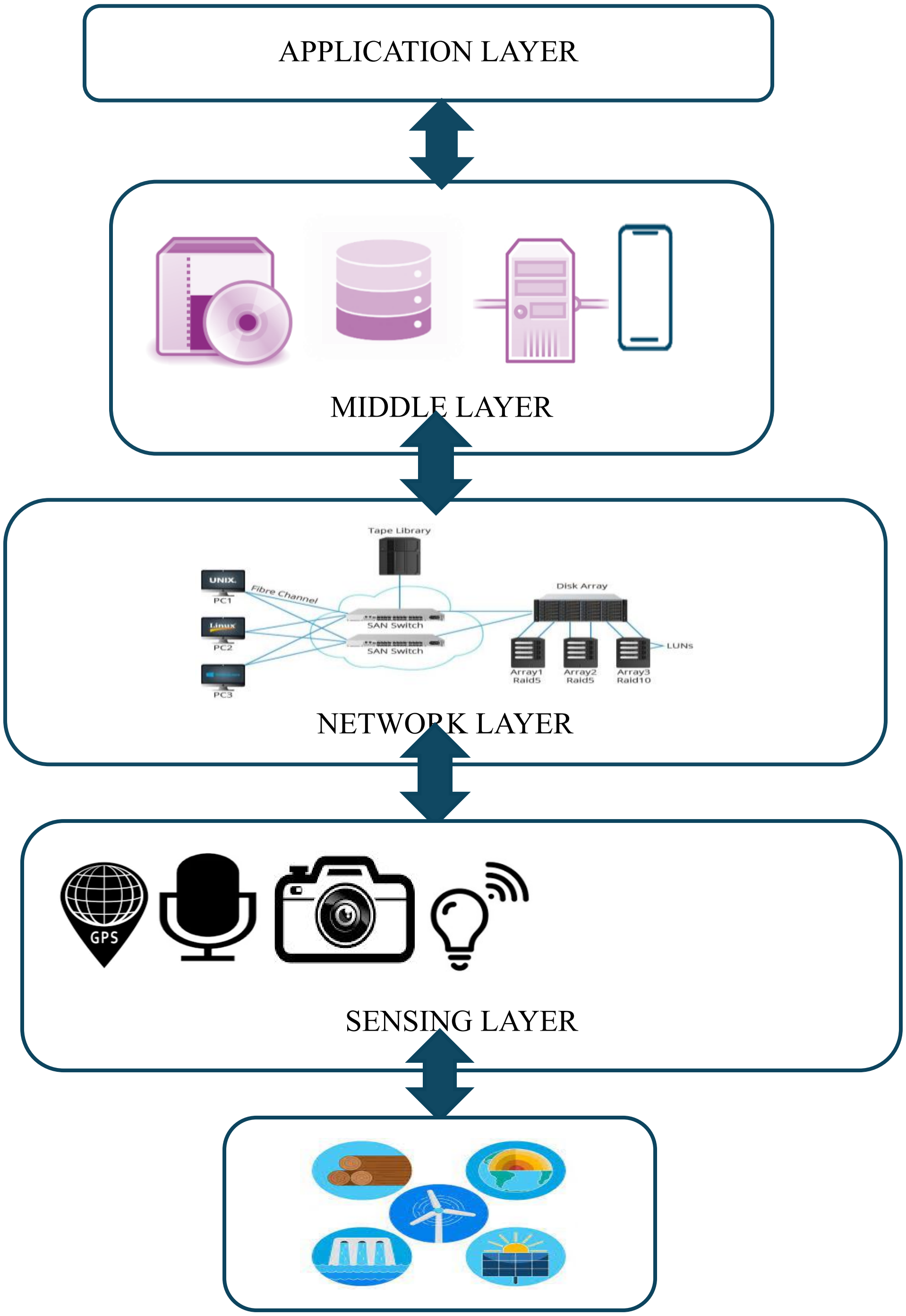


**Fig. 1 IoT layer for renewable energy**

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## Related work

Extensive research has been conducted recently on the application of decentralized composite learning in the Internet of Things, and we review some of these following studies.

Khowaja et al. introduces a DBFL approach (distributed federation learning) that implements scalable and energy-efficient training model exchange. This method uses automated coding of model aggregation to address data heterogeneity and its functional aspects. The results show that this strategy goes beyond centralised federated learning methods regardingprecision and powerprecision.

S.S. Azam et al. introduce afresh coalition learning techniqueknown as TT-HF. This is an federal semi-centric learning technique. In this system, communication with the intended device (D2D) is used for decentralised learning between the device, also the host. During every globalized aggregation cycle, the device sends local model weights over D2D communication within the localizedcluster. Experimental results indicatethat TT-HF improves model precision and reduces system energy consumption in several scenarios of data variability.

M. Obeed et al. proposes the FL-EOCD architecture is designed for distributed federation focusing on energy consumption, using communication and clustering of duplicate devices to devices (D2D). In this context, clusters are no longer confined to the coverage area of individual devices. Devices that overlap between clusters are called bridge devices (BDSS). These clusters are connected by star BDS or in hierarchical topologies, allowing for the distributed provision of segment-specific structures eliminating the necessityfor a central server. The results show that this method improves energy efficiency and reduces learning time relative to hierarchical and star-based strategy.

M.S. Al-Abiadet al. proposed graph theory suggests a centralized and distributed learning method for the Internet drone. This learning approach using iod-Föderat uses the dispersion of localizedspecification between drones in overlapping system regions to facilitate the aggregation in the globalized models. The outcome reveals that a decentralised approach supplies data protection and energy efficiency comparable to that of the centralized approach.

V. Aggarwal et al., Edge-to-cloud distributed training is facilitated by Federation Edge Learning (DFEL) a smart model training procedure that works in conjunction with cloud servers on nodes of edge devices.This method accounts a multi-level, non-uniform apparatus framework with additional local network topology structures that are synchronized over D2D communication. This approach for potential applications such as intelligent factory automation is advantageous and is expected to change the topology from the stellar science to significantly reduce the cost of network resources.



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**Contribution of this work**

This work proposes a new decentralized federal learning architecture, developed specifically for IoT-based renewable energy systems. In contrast to traditional FL methods that rely on central servers, this approach uses a peer-to-peer consensus mechanism to aggregate local models. To ensure the confidentiality of data across the device, we consider privacy techniques that allow techniques such as privacy and secure aggregation to be available. Implement adaptive update strategies and model optimization methods to address communication and energy limitations in IoT environments. Extensive experiments show that our approach reaches the exactness of the competitive design, while synchronously significantly reducing user privacy communication efforts and storage.

The following is a summary of the remaining portion of this paper: The introduction and related works were found in Sections 1 and 2, the suggested approach is described in more attributes in Section 3, the simulation results are shown in Section 4, and conclusion and future research possibilities are elaborated on Section 5.

## Proposed work

Integrating renewable energy sources into IoT-based infrastructure has led to significant advances in energy monitoring, forecasting, and management. However, centralized recording and processing of data from distributed energy systems represents challenges in terms of data protection, communications efforts, delays and system scalability. Federated Learning (FL) offers a promising solution by allowing system to be skilled together unneeded to share raw data. Nevertheless, conventional FL architectures still depend on centralized servers, which introducecritical failure point and require a high degree of trust in the central authority.

This work suggests a new decentralized federal learning (DFL) frame that eliminates the need for central aggregators and allows for cooperative learning of peer-to-peer learning among IoT devices in renewable energy systems. The proposed framework is presentation privacy, scalable, fault-tolerant and energy efficient, to tackle the unique challenges of energy-sensitive boundary environments. and to support robust and distributed intelligence across the network.

The framework of the proposed system is seen in thefigure 2.Federation learning consists primarily of four phases. Local model training, parameter highlighting, teacher model construction, teacher model distribution. In the first step (step 1), each knot initializes the model and performs training using local data. In step 2, each device charges the model output and calculates the central node, particularly using the logit vector from the final softmax layer. This process is inspired by knowledge distillation, along with logit vectors representing knowledge of all edge models.



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As observed in Figure 2, the central node refers only to the nodes selected in this particular training round, not a fixed server. This adaptive selection mechanism deals with data heterogeneity and non-uniform resource distributions on nodes. With high quality node dynamic identification, this framework ensures more effective model aggregation and general training performance.

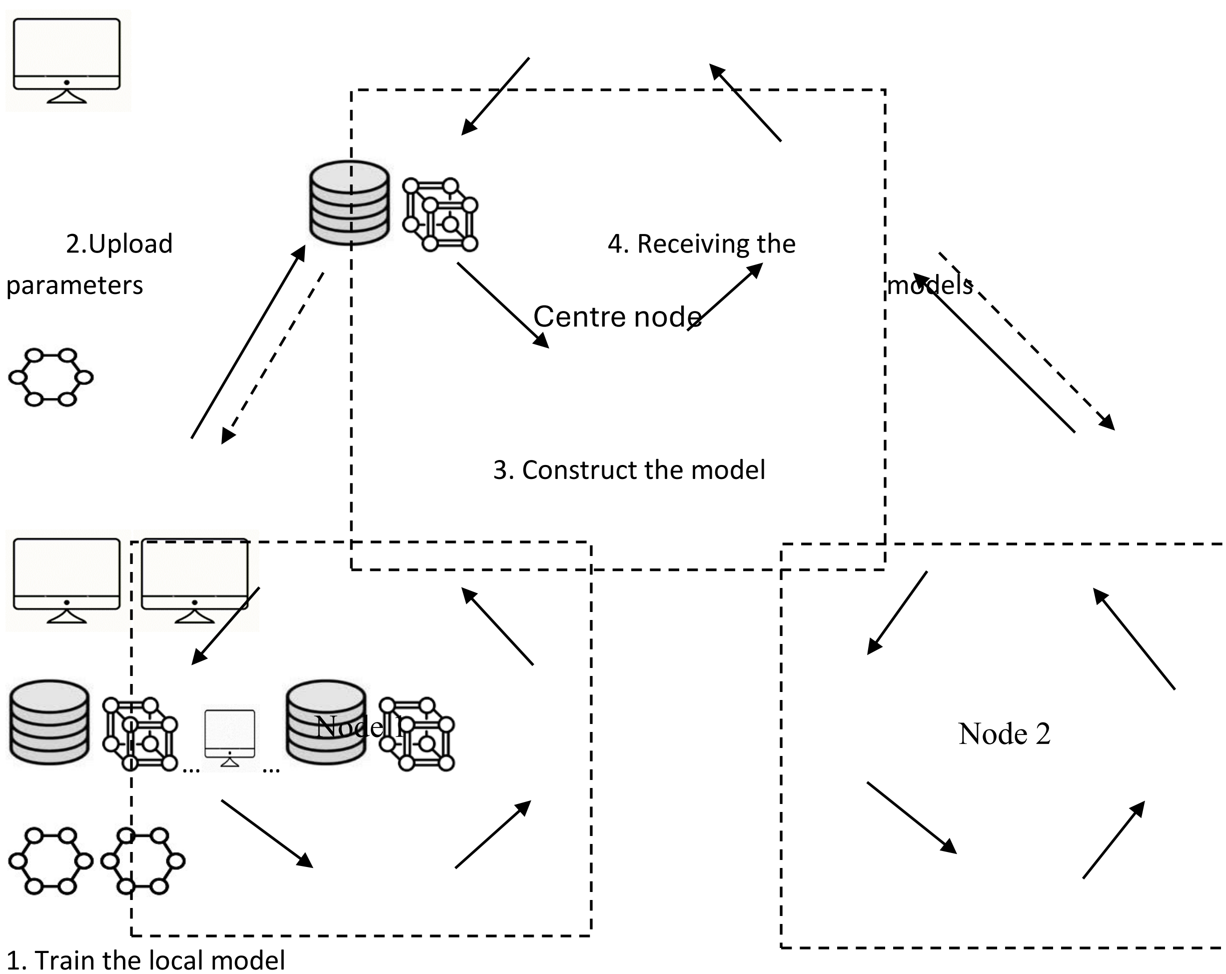


Figure 2 Model of the system

#### 3.1 Decentralised Federated Learning

Considering a system containing number ofnodes, the system can be illustrated by the provided graphG = (node: [n], edge: E) and the adjacent matrix. If the conditions (u, v) ∈ E&(v, u) ∈ E hold node u and v, this refers to the two-way connection between them, allowing for mutual communication. The symbols and notations used in the suggested method is summarized in Table 1.

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**Table 1**

| Symbol | Specification |
|---|---|
| N | Sum of all nodes |
| $S_t$ | The output logits mapped to their respective tags. |
| η | rate of learning |
| ∇ | operator of gradient |
| $L_{total}$ | Aggregate distillation loss |

The network topology is shown in Figure 2. Here, the weights in EmberzMatrix represent bidirectional connection between nodes. If the primary weights are in matrix 1, this means that knots are connected and that weights can change. If the initial weights are in matrix 0, this indicates that the knots are not connected and the weights remain solid. Each knot is either a land node or a different type of computer, and everyone has their own local data and a local model for machine learning.

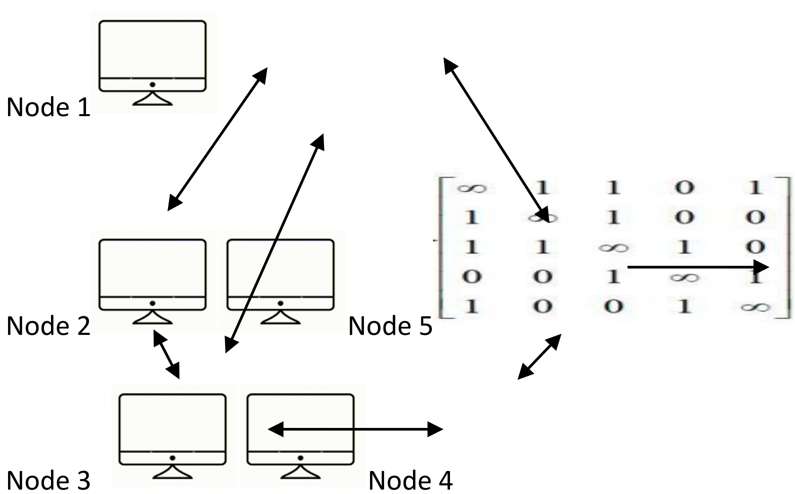


Figure 2. Network topology

Federated training is activated when node functions as a centre node and its neighbors are chosen based on the system architecture. {1, 2, 3,..., N} represents the N nodes, while {D1, D2, D3,..., DN} represents the data. The primary actions of the following of decentralised federated learning:

Step 1: The centre node is determined. The central node is selected by the system in order.



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Step 2: Training a local model. Node k models are trained using local datasets $D_k$. Local system parameters are upgraded at each node via optimization algorithms for gradient discount optimization according to the upgrade rules defined below.

$W_k^{t-1}$- η∇ l $(W_k^t, b) \rightarrow W_k^t$

Where $W_k^{t-1}$ and $W_k^t$ are the model parameter of node k. $(W_k^t, b)$are the node k loss.

Step 3: The node obtains parameter for model.Uploaded in the central node.

Step 4: The model is aggregated. The globalized model is obtained by summarizing the model specification of central node using the model parameters received by the participating node. The federated centre node runs the algorithm 1.

Step 5:Repeat steps 1-4 till the model converges or the stated stopping conditions are met.

**Algorithm 1**
Centreaggregation algorithm
Input: node set K, label set T, maximum number of global model iterations MaxEpoch.
for epoch ← 1 to MaxEpoch do
for k in K do
Average Logits of the node k
for t in T do
$S_k^t \leftarrow S_k^t + S_t^{/k}$
end
end
for k in K do
for t in T do
$S_t^{/k} \leftarrow \frac{S_k^t - S_t^{/k}}{k}$
end
Sending Model Logits
end
end

In Algorithm 1, the logits are displayed as vectors and calculated by the finalizedsoftmaxsegment of the system. These represent logit outputs generated using nodes and marked by student networks. This means that k denotes the number of training nodes that are participating. In the context of distributed



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learning, increasing nodes lists important requirements for the speed of training in machine learning models.

**3.2 Node selection**

With distributed federation learning, the central knot is not fixed and all knots are not as central knots. As a result, the system requires a variety of resources from the node, such as calculations and resources of communication. Therefore, this sub-section focuses on the analysis of node selection methods. A node selection mechanism has been introduced to facilitate efficient application of the proposed spring learning frame, as shown in Fig 3.

In thisstudy, the node selection process is classified into two: centre node selection and adjacent node selection. In all globalized iterations, each node is first trained as a central knot and communicates with its corresponding legitimate neighbour.After completing the training, each knot reports a power metric that serves as the basis for evaluation of the other nodes. Based on these reviews, the greatest score node is chosen as the centre knot for subsequent training rounds. Additionally, the central node evaluates the performance of adjacent nodes, selects the highly rated nodes and acts as the adjacent nodes in the next training. The specific workflows are:

Step 1: All rounds of global iteration select a subgroup of high-quality nodes to participate in spring-based learning. Quantitatively evaluate each node using a variety of metrics. These important metrics are determined based on the output of the local model during the current round and the size of the local data record. Together, it reflects differences in resource heterogeneity regarding data quality and node. Specific language is given as follows:

$$\mu^{t+1} = \frac{\log2(1+\mathrm{dk})}{\mu_k^t}$$

If the local model is performing poorly, this can indicate that no node data is fully used. Improving the use of such data can improve precision.

Step 2: Adjacent matrix is updated. After every knot completed key indicator, the adjacent node updates the auxiliary function and maps the contribution of each neighbor node to the current node using logistic functions.

$$\varphi n(\zeta) = \frac{1}{1+e^{-\beth}}$$

Step 3: Knot Selection. After upgrading Adjenzenz Matrix, the knot with the greatest score for each knot is choose as the centre node for each training cycle. Additionally, nodes with higher values are selected



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as adjacent nodes from the updated adjacent matrix. The parameter ε has been introduced to specify the percentage of adjacent nodes selected in the node selection process.

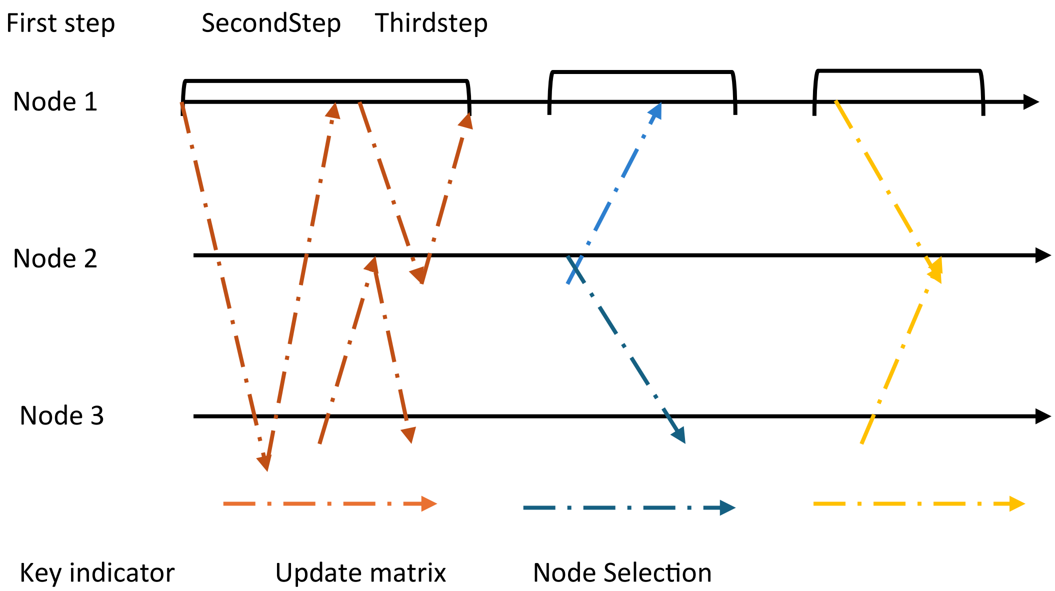


Figure 3. Mechanism of Node selection

The primary distinctions betweenthosetechnique and traditional federated learning frames are as follows: (1) A reporting process for semantic indicators is introduced, and (2) the number of nodes and their locations is dynamically selected by bidirectional selection between nodes. This approach simultaneously retains the benefits of decentralisation and knowledge distillation optimization, drastically decreasing the period of merging. As a result, the cost function converges faster,also ensures a model integration process.

## Result

In this experiment, implementing these extended node selection strategies in distributed FL can significantly improve the performance of IoT-based renewable energy systems. For example, the selection of nodes with optimal energy consumption patterns and arithmetic resources can lead to more accurate predictions of energy requirements and efficient resource allocation in smart grid applications. Furthermore, by addressing challenges such as data heterogeneity and malicious node behaviour, these strategies contribute to system robustness and reliability to ensure sustainable and efficient energy management.

The experiment takes into account two cases where training data for different nodes IIDs and are not IIDs. For IID sets, the data is mixed then distributed randomly across all knots. For non-IID sets nodes are limited to accessing predefined data categories with two local labels, and 500 data pieces are split into groups



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within each category. The node randomly selects three setfor each group such as local data. Those data partition allows you to investigate the robustness of the proposed methods of data using non-uniform distributions.

In the context of distributed learning, blockchain-based learning had chosen like a standard in favour of comparative assessments. Its decentralized, invariant nature makes it a reliable and secure framework for the implementation of the latter.

Experimental setup 1: Comparing accuracy of various algorithms under IID data distributions.

If the data which are distributed is IID, the average precision of each system is displayed forvarious cycle in Table 3. It can be seen that improvingthe count of rounds for different data records improves the average accuracy of each method.

Centralised federated learning, by contrast,**blockchain-based decentralised approach** demonstrates notable improvements in accuracy on the **MNIST dataset.** Specifically, it achieves gains of **14.95%, 10.15%,** and **10.12%** at training rounds **10, 30,** and **50**, respectively. Similarly, accuracy improvements of **16.3%, 16.67%,** and **8.68%** are observed at the same rounds under additional testing conditions.

Table 2Experiment of IID control

| Data resource | Approach | Accuracy of 10 round | Accuracy of 30 round | Accuracy of 50 round |
|---|---|---|---|---|
| MNIST-IID | CFL | 54.27% | 77.27% | 79.35% |
| | FD | 58.31% | 79.23% | 78.24% |
| | BD | 69.22% | 87.42% | 87.44% |
| | FP | 55.14% | 78.34% | 79.57% |
| | Method proposed | 65.48% | 84.76% | 88.60% |

Figure 4 shows the accuracy curves for individual nodes across the training round using the suggested method. The outcomepresent that the ideal number of training cycles ranges from 30 to 40. If the number of node remains stable, an increase in training rounds will lead to a significant advancement in the identification precision of all nodes.



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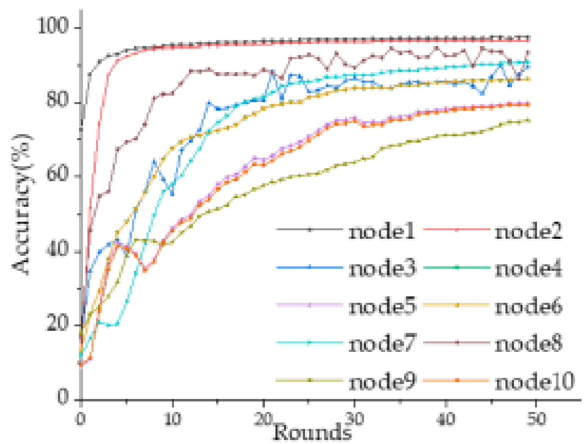


Figure 4. Node accuracy under IID

Experimental setup 2: Using Non-IID data distribution, accuracy experiments under various algorithms.

Here, the improved method generalizes is evaluated and the datasare distributed in a Non-IID method. Table 3 presents a comparison of the overall model accuracy.

Table 3

Experiment of Non-IID control

| Dataset | Approach | Accuracy of 10 round | Accuracy of 30 round | Accuracy of 50 round |
|---|---|---|---|---|
| MNIST-Non -IID | CFL | 46.35% | 64.19% | 75.26% |
| | FD | 49.27% | 69.74% | 71.74% |
| | BD | 50.97% | 79.04% | 85.13% |
| | FP | 47.63% | 67.92% | 72.55% |
| | Method proposed | 48.94% | 77.83% | 83.19% |

Using the dataset of MNIST, the blockchain-based decentralized approach enhances performance of the model by 3.62%, 11.99%, and 14.99% after each training rounds, respectively, when contrasted to centralised federated learning. After 50 rounds, the suggested method reaches a model accuracy of 84.16%.



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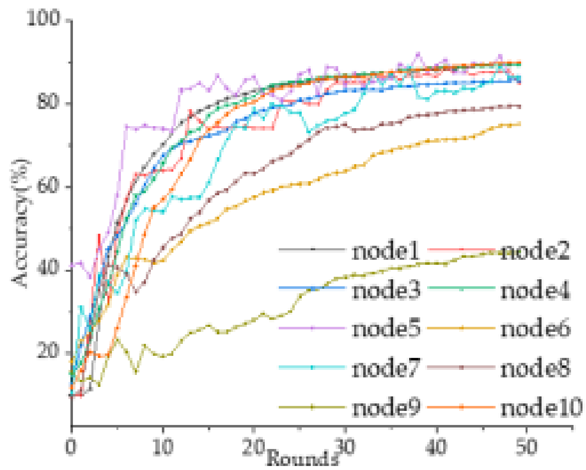


Figure 5. Node accuracy under Non-IID

Each node, model accuracy is shown in Figure 5. If the data distribution followsa Non-IID pattern, accuracy of the model shows a slight decrease in comparison to the IID setting. A centre learning method in which the centre node assumes medium weight has a detrimental impact on the model. However, distributed learning method of node selection suggested in this paper can improve local model more effectively, leading to a general improvement in model accuracy.

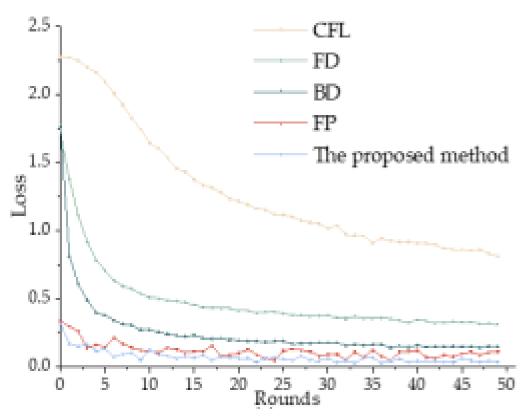


Figure 6. Loss on datasets

Figure 6 shows the loss results based on various data records. If count of iteration cycles is kept below 45, this method shows a slightly better convergence rate compared to the other three methods, then this article can converge this method. At the same time, this method reaches a low loss for both data records. In MNIST data records, the loss of this method is about 0.08 This method achieves a loss of 0.03 on the



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CIFAR 10 dataset. Furthermore, you can achieve a loss of 0.04 with fewer data records than the other three approaches.

Experimental setup 3:

Verification of Scale Selection.

The experiments compared runtimes of centralized federated learning methods, and how to select blockchain and decentralized methods, federated distillation methods, and decentralized spring learning node selection methods with different numbers of knots. The experimental outcomes are seen in fig 7.

In thissuggested method effectively selects high quality nodes for model aggregation, thus ensuring a certain number of nodes when processing a certain number of nodes.

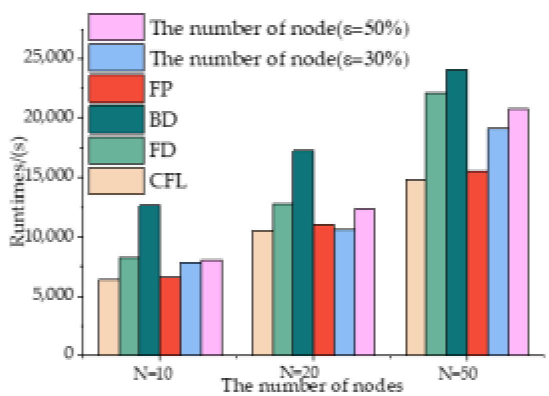


Figure 7. Runtime based on the number of nodes

### Conclusion

Full synchronization in a centralized network is a challenge.If the data distribution between nodes differs significantly, the central server could mean directly varying parameters directly, resulting in less accurate model. This paper proposes a node selection-based distributed learning method as a solution to the problem.This study examined distributed federated learning (FL) frames tailored to IoT-enabled renewable energy systems, and focused on intelligent node selection. Our approach emphasizes minimizing communication efforts, improving system robustness, and optimizing energy consumption for all critical aspects in a distributed smart grid environment. By using an efficient node selection mechanism, only the most reliable and energy efficient nodes are involved in the data protection data protection and training process that maintains model accuracy and convergence speed. Additionally, node selection



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based on real-time resource availability and historical performance metrics has enabled adaptive learning and energy production patterns.

**Reference**

[1] Zhang, C.; Xie, Y.; Bai, H.; Yu, B.; Li, W.; Gao, Y. A survey on federated learning. Knowl.-Based Syst. 2021, 216, 106775

[2] Tedeschini, B.C.; Savazzi, S.; Stoklasa, R.; Barbieri, L.; Stathopoulos, I.; Nicoli, M.; Serio, L. Decentralized federated learning for healthcare networks: A case study on tumor segmentation. IEEE Access 2022, 10, 8693–8708.

[3] Lu, Y.; Huang, X.; Dai, Y.; Maharjan, S.; Zhang, Y. Federated learning for data privacy preservation in vehicular cyber-physical systems. IEEE Netw. 2020, 34, 50–56.

[4] McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; y Arcas, B.A. Communication-efficient learning of deep networks from decentralized data. In Artificial Intelligence and Statistics; JMLR: Norfolk, MA, USA, 2017; pp. 1273–1282.

[5] Zheng, L.; Huang, Y.; Zhang, W.; Yang, L. Unsupervised Recurrent Federated Learning for Edge Popularity Prediction in Privacy-Preserving Mobile-Edge Computing Networks. IEEE Internet Things J. 2022, 9, 24328–24345.

[6] Li, T.; Sahu, A.K.; Zaheer, M. Federated optimization in heterogeneous networks. Proc. Mach. Learn. Syst. 2020, 2, 429–450.

[7] Zhang, J.; Chen, J.; Wu, D.; Chen, B.; Yu, S. Poisoning attack in federated learning using generative adversarial nets. In Proceedings of the 2019 18th IEEE International Conference on Trust, Security and Privacy in Computing and Communications/13th IEEE International Conference on Big Data Science and Engineering (TrustCom/BigDataSE), Rotorua, New Zealand, 5–8 August 2019; pp. 374–380.

[8] Kairouz, P.; McMahan, H.B.; Avent, B.; Bellet, A.; Bennis, M.; Bhagoji, A.N.; Zhao, S. Advances and open problems in federated learning. Found. Trends Mach. Learn. 2021, 14, 1–210.

[9] Chen, X.; Lan, P.; Zhou, Z.; Zhao, A.; Zhou, P.; Sun, F. Toward Federated Learning With Byzantine and Inactive Users: A Game Theory Approach. IEEE Access 2023, 11, 34138–34149.

[10] Lian, X.; Zhang, C.; Zhang, H.; Hsieh, C.J.; Zhang, W.; Liu, J. Can decentralized algorithms outperform centralized algorithms? a case study for decentralized parallel stochastic gradient descent. In Advances in Neural Information Processing Systems; NIPS Foundation: La Jolla, CA, USA, 2017; Volume 30, pp. 5336–5446.

[11] He, C.; Tan, C.; Tang, H.; Qiu, S.; Liu, J. Central server free federated learning over single-sided trust social networks. arXiv 2019, arXiv:1910.04956.

[12] Yubo, S.O.N.G.; Jingkai, Z.H.U.; Lingqi, Z.H.A.O.; Aiqun, H.U. Centralized federated learning model based on model accuracy. J. Tsinghua Univ. Sci. Technol. 2022, 62, 832–841. 13. Caldarola, F.; d'Atri, G.; Zanardo, E. Neural Fairness Blockchain Protocol Using an Elliptic Curves Lottery. Mathematics 2022, 10, 3040.

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