International Journal of Electrical and Electronics Engineers
Volume 14, Issue No. 02, July-Dec 2022
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

ARTIFICIAL INTELLIGENCE AND FEDERATED LEARNING IN WIRELESS

Salman Hilal Bhat [1], Ritesh Kumar Ojha[2]

[1]PG-Digital Communication Engineering, Mewar University, Chittorgarh, Rajasthan

[2]Assistant professor & Head department of Electronics & Telecommunications, Mewar University, Chittorgrah, Rajasthan

[1]salmankashmiri56@gmail.com, [2]riteshojha3@gmail.com

Abstract

In this paper we study About Wireless Networks in Distributed Artificial Intelligence and Federated Learning. Federated Learning (FL), where model training is dispersed among mobile users, is gaining popularity.UEs' local computation and training data despite protecting data privacy, FL contains heterogeneous UE data and assets first; we suggest FEDL can handle diverse UE data. strong convex and smooth losses We give a convergence UE update local computation rounds local model and global communication circles FL model. Wireless networks use FEDL as a resource allocation optimization FEDL convergence time and energy trade-off UE power and computing consumption resources.

Problem with wireless resource allocation We take use of FEDL's structure because it is not convex. Examine the closed-form solutions to the three sub problems that it can be divided into. Finally, we assess FEDL and Py Torch convergence. Experiments and numerical results Wireless resource allocation issues. Results FEDL outperform Fed Avg Different parameters' convergence rate and test accuracy. Shows evolutionary (genetic method) network clustering Models and parameters are provided first. The further chapter discusses optimum network partitioning. The paper describes the simulation environment for protocol implementation and analysis. The fuzzy c-means clustering technique is presented here for the purpose of optimizing the routing protocol in wireless sensor networks.

Keywords: *Artificial intelligence, Wireless, leach, WSN, Network, Algorithm, signal*

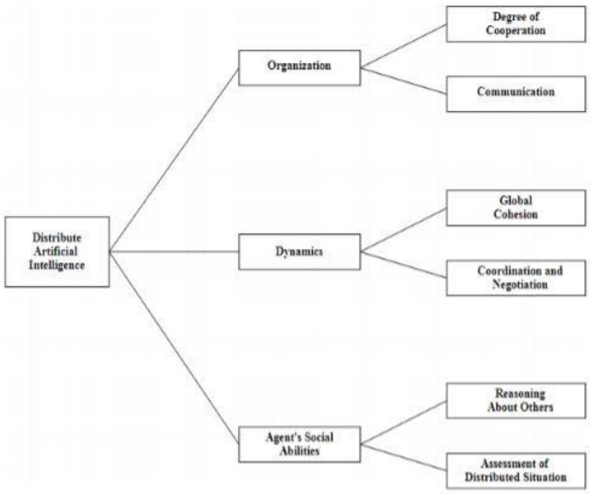
1. INTRODUCTION

1.1 OVERVIEW

Machine learning techniques have recently drawn a lot of attention as important enablers for next-generation wireless networks. The majority of machine learning approaches used by wireless systems nowadays are centred on centralising the training and inference processes by moving the data from the end devices to a third party centralized location. However, these techniques result in privacy leakage on end-devices. One can utilize distributed machine learning at the organization edge to take care of these issues. One of the main distributed learning calculations in this setting is federated learning (FL), which empowers gadgets to train a typical machine learning model while retaining nearby duplicates of the information. However, there are other research topics that need to be address edinorder to implement FL in wireless networks and improve performance. For instance, in FL, wireless links are required for communication between wireless devices and edge servers during the training of machine learning models. As a result, wireless impairments such varying wireless channel statuses, interference, and noise have a big impact on FL's performance. For instance, interference alignment, resource management, clustering, and network control are just a few examples of complicated optimization problems that can be solved using federated reinforcement learning, which makes advantage of distributed computing power and data. Due of the high expense of model training, FL traditionally takes the unrealistic assumption that edge devices will always engage in tasks when asked. Because of its solid capacities and potential applications, federated learning is becoming an ever increasing number of appealing in the fields of wireless correspondences and machine learning. Federated learning uses correspondences between the focal server and the distributed neighborhood clients to train and improve a machine learning model, as opposed to other machine learning procedures that don't require correspondence assets. Performance optimization therefore depends on knowing how to allocates carce communication resources to training a federated learning model effectively. As a brand-new technique, federated learning, however, can possibly work on the intelligence of wireless networks.

DISTRIBUTEDARTIFICIALINTELLIGENCE

The investigate on of allocating, coordinating, and forecasting the execution of errands, objectives, or choices in a multi-specialist frame work is known as distributed artificial intelligence (DAI). DAI, which began as an area of artificial intelligence roughly 25 years ago, has developed into a separate field of study that combines concepts from those fields as well as economics, psychology, sociology, operations research, and organizational theory. The essential focal point of DAI research has been on modeling the information, correspondence, and dynamic cycles expected to help social orders of computational specialists or half and halves of people and PCs in information economies. The two main classifications of this examination are distributed critical thinking and multi-specialist frame works. Distributed critical thinking tends to these difficulties by dividing the assignment among a few helpful issue solvers who share the computational burden and know about one another's half way arrangements. In distributed critical thinking settings, the interaction between individual hub so rissue solvers is



obviously depicted. On the other hand, multi-agents systems are interested in how loosely coupled problem solvers, or agents, behave when they cooperate to find a solution to a problem that is outside the scope of any one of them. Given their sensory and operational capabilities, these autonomous entities also known as computational agents are in dependent problem solvers with the capacity to act intelligently in a variety of environmental contexts. The way that DAI combines the computational assets of an assortment of specialists so the gathering intelligence surpasses the capacity of the individual specialists is a key element. This description assumes that each individual agent has some intelligence, however little. While coordinating, cooperating, negotiating, or engaging in contest with different specialists, the specialists utilize this intelligence, or ability to settle on taught choices in view of a model of the world and the accessible information. It should be noted that a central controller does not dictate how agents must interact. Depending on the environment of the application and the ultimate objective, the agents may have cooperative or competitive personalities. For instance, specialists representing a market economy with independent makers and clients might be best depicted by serious specialists; however specialists representing assets in an association fully intent on improving the productivity of the association might require helpful specialists.

SCOPEOFTHESTUDY

The proposed study focuses on the clustering technique's optimization of the routing protocol using factors like location data, residual energy, and received signal strength. Signal quality is assessed using the received signal strength. To ascertain how much energy is still in the sensor nodes, residual energy is measured. The position information of the sensor nodes is known using location data. Additionally, a Meta heuristic algorithm is used to guarantee global minima.

1.7 OBJECTIVES OFTHE STUDY

This study focuses on federated learning and distributed artificial intelligence in wireless sensor networks. The primary goals of this research project are:

RESEARCH METHODOLOGY

In order to research current clustering issues and optimization methods in wireless sensor networks. Maximizing network lifetime is the main design goal for power-constrained WSNs. WSN clustering facilitates data processing within networks and controls energy usage. Numerous cluster-based network layer protocols have been created in an effort to prolong network life, however cluster optimality is a pre requisite for these protocols' efficiency in energy management. It is NP-hard to cluster sensor nodes in the optimal way. In order to create effective wireless sensor network clusters, this chapter introduces a multi-parameter cluster optimization technique based on evolution aryalgorithm models.

- **System Models**

Sensor node energy dissipation is caused by microcontroller energy consumption for data aggregation and signal transmission or reception.

International Journal of Electrical and Electronics Engineers
Volume 14, Issue No. 02, July-Dec 2022
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

Performance Assessment

The simulation results of the suggested method are discussed in this section in terms of various network performance metrics, including throughput, energy balance, and network lifetime. The studies' findings demonstrate that the method outperforms LEACH and LEACH-C . During the simulation, the sensor only makes use of energy for data aggregation, transmission, or reception. We presume to have a clear line of communication. Additionally, the energy lost in wireless channel collisions and interference is not considered

EVOLUTIONARY and OPTIMIZATION

When building network protocols for power-constrained WSNs, the most important consideration is how to maximize the network's lifetime. In-network data processing is made possible by the division of WSNs into several clusters, which also helps to keep the network's overall power consumption under control. The effectiveness of clustering in energy management is heavily dependent on the optimality of clusters, despite the fact that several cluster-based network layer protocols have been created in an effort to extend the lifetime of networks

SYSTEMMODELS

The use of energy, the propagation of radio waves, and the network models that are considered in this chapter are all comparable to models. Therefore, the source of energy loss in sensor nodes is the consumption of electrical power by the microcontrollers during the process of data aggregation, as well as the consumption of electrical power during the transmission or receiving of signals

PERFORMANCEEVALUATION

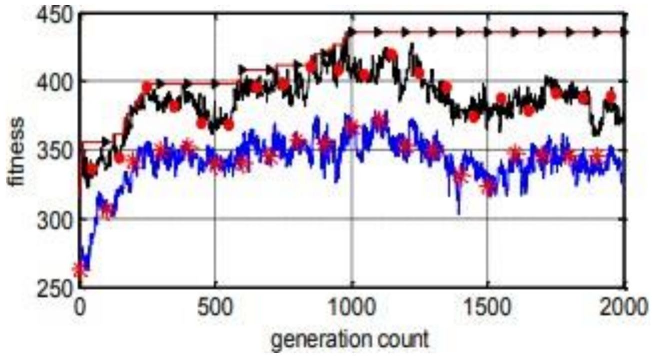
This section presents the findings from our simulations of the suggested approach in terms of a number of network performance indicators, such as network longevity, energy balance, and through put. The experiment's results show that the algorithm performs better overall than both the LEACH and LEACH-C procedures. During the experiment, the only time the sensor used any energy was when it was transmitting, receiving, or aggregating data. We have presumed that the communication channel is fault free. In addition, the energy loss that occurs as a result of interference and collision in the wireless channel is not taken in to consideration.

4.5.1 Simulation Environment

The $\mathrm{OMNeT}++$ simulation platform is utilized in the carrying out of the experiment. For the purpose of putting the protocol in to action, the fuzzyc-means clustering and genetical gorithm toolboxes have been constructed in C++ and integrated with the $\mathrm{OMNeT}++$ simulation environment. Within a WSN region that is $100\ m\times 100\ m$ in size, there are networks of one hundred sensor nodes each. During the simulation, the following configuration parameters were utilized : initial energy=2J,basestationlocation=(175,50)m, control packet size=25 bytes, data packet size =500 bytes, E_{elc}= 50nJ/bit, energy loss for data aggregation (Eda) =5nJ/bit/signal, efs = 10pJ/bit/m^2, emp = 0.0013pJ/bit/m^4, and TDMA frames per round = In the experiment, the population size was set at 50, the mutation rate was 0.001, the crossoverratewas0.8, and thegeneration countwassetat2000.

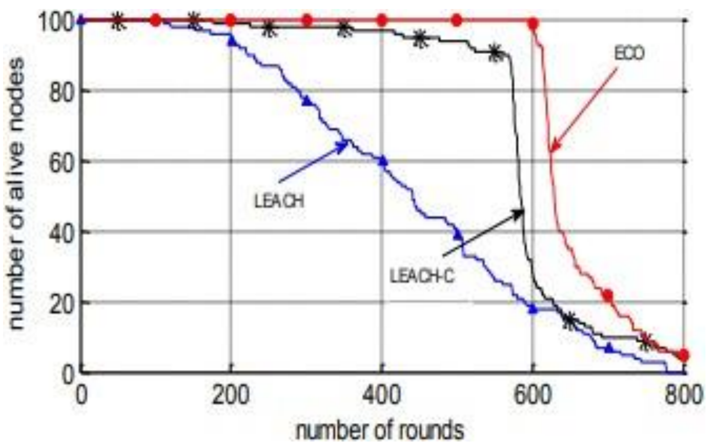
4.5.2 Experimental Results and Analysis

The genetic algorithm is carried out in an iterative fashion by the base station up until the convergence condition has been met. Figure 4.1 is a figure that illustrates the lowest and maximum fitness of chromosomes for each generation, as well as the greatest fitness that has ever been recorded in the annals of generations for a data collection round that was chosen at random. When the algorithm first begins, the value of fitness has a tendency to grow very rapidly. However, as the iteration continues until the convergence point, the algorithm scarcely exhibits any progress in the value of fitness. According to the findings of the simulation, the algorithm achieves convergence after a period of 1000 generations has passed for the chosen data gathering cycle.



Fitness of chromosome pereach generation

The death rate of nodes in ECO is higher than the death rate of nodes in other networks afterthedeathofthefirstnodeorevenafterfiftypercentofthenodeshavediedwhenitisaveragedfrom the time at which the first node fails or fifty percent of the nodes have died until nearly all of the nodes have died. Following the loss of the initial node, the network is often seen as being unstable, even if its quality does not rapidly deteriorate at a significant pace. Therefore, the ECO method is superior than LEACH and LEACH-C protocols in terms of increasing the size of the stable zone. The amount of time that has passed since a certain percentage of nodes reached their end of life is detailed in Table 4.1for each of the three protocols.



International Journal of Electrical and Electronics Engineers
Volume 14, Issue No. 02, July-Dec 2022
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

Number of alive nodes versus time

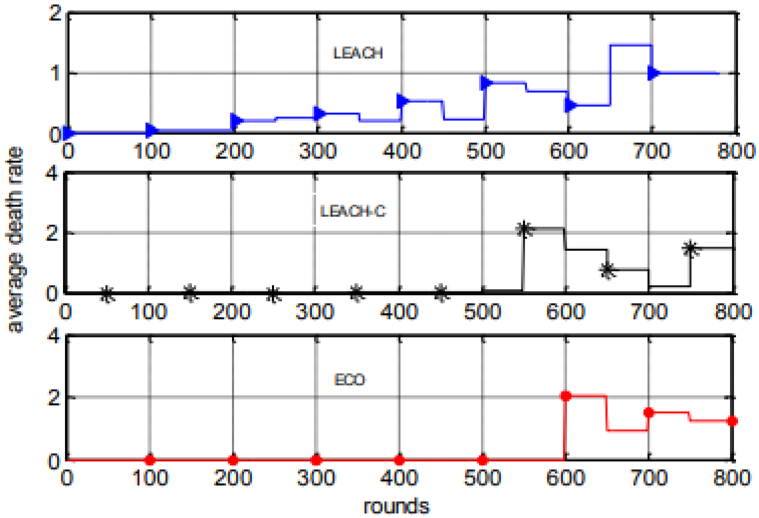


Figure4.3:Deathrateofnodes versustime

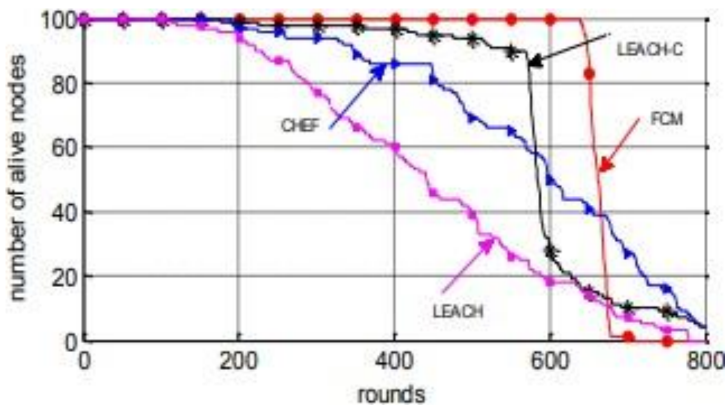
Table 4.1: Summary of FND, PND and LND metrics for LEACH, LEACH-C and ECOprotocols

Metric	**LEACH**	**LEACH-C**	**ECO**
FND	111	178	601
20% of nodesdie	288	576	619
40% of nodesdie	400	582	625
HND	441	585	631
60% of nodesdie	502	590	641
80% of nodesdie	593	629	706
LND	778	810	811

International Journal of Electrical and Electronics Engineers
Volume 14, Issue No. 02, July-Dec 2022
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

EXPERIMENTALRESULTSANDDISCUSSION

The OMNeT + + simulation tool is utilized in the process of implementing the protocol. The WSN area is 100m×100m, and there area total of N(N=100) sensor nodes spread out over the region. During the simulation, the following values were used for the parameters : initial energy =2J, base station location =(175,50)m, control packet size =25bytes, data packet size=500bytes, $Eelc$=50nJ/bit, energy loss for data aggregation(Eda)=5nJ/bit/signal, efs =10pJ/bit/m^2, emp = 0.0013pJ/bit/m^4, and TDMA frames per round = 6 In the simulation, we are looking at the overall quantity of energy consumed by nodes, the variance in energy consumption across different nodes, and the number of working nodes that are present in each round. In wireless sensor networks, the network life span is an important parameter that is used to measure the performance of the protocols. The point in time when the network has lost fifty percent of its nodes has been chosen as the defining moment for the network's life time, as was discussed in earlier chapters. Figure 4.9 provides a visual representation of the number of functioning sensor nodes that are found in each cycle. In comparison to LEACH, LEACH-C, and CHEF protocols, the results of the simulation show that the suggested protocol extends the lifetime of the network by 50.45%, 13.36%, and 10.52% correspondingly. In terms of the FND metric, the FCM-based protocol is likewise successful in defeating the LEACH, LEACH-C, and CHEF procedures. For the LEACH, LEACH-C, CHEF, and FCM protocols, the amount of time that has transpired since the indicated proportion of nodes have perished may be found in Table 4.2.



Functional nodes per simulation rounds

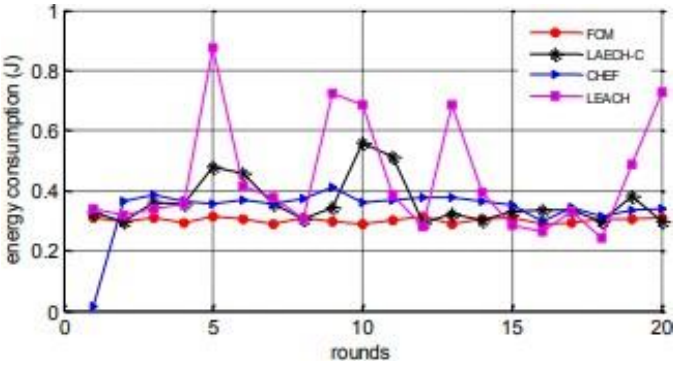
Figure 4.9: Table 4.2: Summary of FND, PND and LND metrics for LEACH, LEACH-C,CHEF and FCM protocols.

Metric	**LEACH**	**LEACH-C**	**CHEF**	**FCM**
FND	111	178	190	641
20%of nodesdie	288	576	454	653
40%of nodesdie	400	582	570	658

International Journal of Electrical and Electronics Engineers
Volume 14, Issue No. 02, July-Dec 2022
ISSN (O) 2321-2055
ISSN (P) 2321 -2045

HND	441	585	600	663
60%of nodesdie	502	590	656	668
80%of nodesdie	593	629	685	673
LND	778	810	820	708

In WSNs, there should be a balance between the energy dissipation that occurs between nodes in order to prevent the early death of nodes. Utilizing the difference in residual energy across nodes in each cycle, an analysis has been performed to determine the current state of load balancing in the network. The results of the simulation that are represented in Figure4.10 show that the FCM-based protocol is superior to the LEACH protocol, the LEACH-C protocol, and the CHEF protocol when it comes to load balancing in the network. In the simulation, we also take into account the overall amount of energy that nodes consume during each round. In Figure4.11, a comparison of the total amount of energy consumed by nodes for each protocol is carried out using 20 cycles that are selected at random. The findings of the simulation show that the suggested protocol has a much reduced energy consumption of nodes compared to its alternatives.



Total energy consumption of nodes versus time

CONCLUSION

In wireless sensor networks (WSNs), there are many different routing techniques, but the routing protocols that are based on cluster formation not only ensure the least amount of energy consumption possible but also regulate the scalability of the networks. Clustering nodes in such away that they would create an ideal configuration is not an easy process since wireless sensor networks are formed from devices that are scattered and self-organized. This thesis tackles some of the most difficult issues that arise in the process of clustering. It is well known that the NP-hard combinatorial optimization issue that pertains other optimal arrangement of nodes in WSNs. Because the solution space for NP-hard issues is so huge, exhaustive or direct search methods are unable to provide an optimal solution in a timeframe that is polynomially constrained. Large-scale network problems fall into this category The optimization challenge presented in the first contribution entails partitioning the network into the best possible collection of clusters in order to achieve the greatest possible extension of the lifetime of the network. One of the parameters for optimization, along with the cluster balance among cluster heads and the energy efficiency of cluster heads, is the communication distance between normal nodes and cluster leaders

- The experimental research findings show that the CPSO and CSA processes outperform the popular LEACH-C methodology. Additionally, it has been noted that the CPSO protocol predominates over the CSA protocol.

The evolutionary-based optimum division of networks is the second contribution that was made with reference to the optimal layout of clusters. A novel method to the formulation of the optimization problem in the clustering of networks into the best possible structure has been created. The fuzzy c-means clustering algorithm is launched as soon as the geographical positions of the nodes are obtained to do the initial calculations required to identify the cluster centres. Finding cluster centres can be thought of as a nonlinear optimization problem with limitations The nodes that are most closely located to the centers of clusters are the ones that are considered to be candidates for the role of cluster head. The protocol ensures that nodes are partitioned in to clusters in the most effective manner.

REFERENCES

[1] Z. Li, B. Liu and W.Wang, MEMS processingand Fabrication Techniques andTechnology:SiliconbasedMicromachining.MicrosystemsandNanotechnology,SpringerBerlin Heidelberg, pp. 287-352, 2012.

[2] H.Karl andA. Willig,Protocolsandarchitecturesforwirelesssensor networks.Chichester:Wiley, 2005.

[3] D. Chu, A. Deshpande, J. Hellerstein, and W. Hong, “Approximate Data Collection inSensor Networks using Probabilistic Models,” 22nd International Conference on DataEngineering(ICDE'06), 2006.

[4] C.-F.Chiasserini andM.Garetto,“Modelingtheperformance ofwirelesssensornetworks,”IeeeInfocom, 2004.

[5] M.N.Halgamuge,M.Zukerman,K.RamamohanaraoandH.L.Vu,“Anestimationofsensor energy consumption,” Progress in Electromagnetics Research B, vol. 12, pp.259-295, 2009.

[6] A. Woo and D. E. Culler, “A transmission control scheme for media access in sensornetworks,”Proceedingsofthe7thannualinternationalconferenceonMobilecomputingand networking-MobiCom'01, 2001.

[7] W. Ye, J. Heidemann, and D. Estrin, “An energy-efficient MAC protocol for wirelesssensor networks,” Proceedings.Twenty-First Annual Joint Conference of the IEEEComputerand CommunicationsSocieties, 2002.

[8] T. V. Dam and K. Langendoen, “An adaptive energy-efficient MAC protocol forwirelesssensornetworks,”ProceedingsofthefirstinternationalconferenceonEmbeddednetworked sensor systems- SenSys'03, 2003.

[9] M.MillerandN.Vaidya,“AMACprotocoltoreducesensornetworkenergyconsumption using a wakeup radio,” IEEE Transactions on Mobile Computing, vol. 4,no. 3, pp. 228–242, 2005.

[10] H.Venkataraman,G.M.Muntean,GreenMobileDevicesandNetworks:EnergyOptimizationand Scavenging Techniques, CRCPress, 2012.

[11] S. Roundy, P. K. Wright, and J. M. Rabaey, “Energy Scavenging for Wireless SensorNetworks,”2003.

[12] M. Keating and P. Bricaud, Reuse methodology manual for system-on-a-chip designs.Boston:Kluwer Academic, 2000.

[13] R. Saleh, S. Wilton, S. Mirabbasi, A. Hu, M. Greenstreet, G. Lemieux, P. Pande, C.Grecu, and A. Ivanov, “System-on-Chip: Reuse and Integration,” Proceedings of theIEEE,vol. 94, no. 6, pp. 1050–1069, 2006.

[14] K.AkkayaandM.Younis,“Asurveyonroutingprotocolsforwirelesssensornetworks,”Ad HocNetworks, vol. 3, no. 3, pp. 325–349, 2005.

[15] G. Asada, M. Dong, T.S. Lin, F. Newberg, G. Pottie, W.J. Kaiser and H.O Marcy, “Wireless integrated network sensors: Low power systems on a chip,” Proceedings ofthe24th European Solid-StateCircuits Conference(ESSCIRC), 1998.