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Energy-Efficient Selective Opportunistic Routing (EESOR) for Enhanced Network Lifetime and Reduced Delay in Mobile Ad Hoc Networks

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ABSTRACT: Energy consumption is the main limitation when it comes to mobile ad hoc networks. Battery depletion is the primary cause of sensor node failures since they are placed in rugged terrain with variable environmental conditions, and battery replacement is typically not an option. Therefore, it will be prudent to employ a suitable routing algorithm to identify the optimal path that uses the least amount of energy and minimizes the delay. Opportunistic Routing is one such kind of routing protocol. By choosing the node that records the packet transmission, this routing method dynamically determines each packet, each hop, and the subsequent relay node. In this case, each node has a list of next hop nodes known as the forwarder list, from which the next relay node is chosen based on the kind of opportunistic Routing (EESOR) lowers the size of the forwarder list. The following phase involves sorting the list based on how far away each node is from the destination. The node with the highest priority will be the next relay node, meaning that the chosen relay node will be the one closest to the destination. In terms of network lifetime and end-to-end latency, it outperforms a number of current opportunistic routing systems.

KEYWORDS: dynamic federated learning, global mobile edge computing, decentralized machine learning, EESOR

I. INTRODUCTION

Model training across a network of devices is made possible by Dynamic Federated Learning (DFL), a potent paradigm for collaborative machine learning in decentralized environments that eliminates the requirement for centralized data collection. The incorporation of DFL becomes especially important in the setting of Global Mobile Edge Computing (GMEC), where computational duties are offloaded to the network's edge. The innovative use of dynamic federated learning for GMEC in situations including time-varying wireless networks is examined in this paper. Maintaining the effectiveness and precision of collaborative learning requires federated learning models to be adjusted to the dynamic settings of mobile devices, which are always moving and undergo wireless connectivity fluctuations. In order to guarantee optimal performance in dynamic and changing mobile environments, this research attempts to improve the robustness and adaptability of federated learning models, addressing the difficulties presented by the temporal variability of wireless networks in the GMEC context.

1.1 DYNAMIC FEDERATED LEARNING

An inventive method of federated learning called Dynamic Federated Learning (DFL) tackles the difficulties presented by dynamically shifting surroundings, especially when it comes to remote and decentralized systems. By training machine learning models across a network of dispersed devices, federated learning enables cooperative learning without centralizing the raw data. By adjusting to the dynamic nature of these environments where factors like network connectivity, device availability, and data distribution may alter over time DFL expands on this idea. The ability to respond to changes in data availability, maintain model correctness and efficiency in the face of changing circumstances, and dynamically modify model training parameters based on the present status of participating devices are some of Dynamic Federated Learning's primary characteristics. Since these environments frequently display unpredictability due to elements like mobility, sporadic connectivity, and shifting data distributions, DFL is especially pertinent in scenarios involving mobile devices, IoT devices, or edge computing nodes. DFL's flexibility helps





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federated learning models be resilient, which guarantees that they function at their best in dynamic, real-world environments.

1.2 GLOBAL MOBILE EDGE COMPUTING

In the context of mobile networks, Global Mobile Edge Computing (GMEC) is a distributed computing paradigm that expands edge computing's capabilities to a global scale. By processing data closer to where it is generated or consumed, edge computing lowers latency and improves the functionality of apps and services as a whole. By adding a global viewpoint, GMEC expands on this idea and makes it possible for geographically dispersed edge computing nodes in a mobile network to collaborate and share resources with ease. The network's edge, which consists of a network of mobile devices, base stations, and other edge computing equipment, is where GMEC offloads computational duties. This method makes use of the computer resources' close proximity to end users and devices, allowing for quicker reaction times and increased productivity. In the context of developing technologies like 5G networks, where the requirement for high-bandwidth, low-latency services is fueling the desire for more potent and widely dispersed computing capabilities, GMEC is especially pertinent.

1.3DECENTRALIZED MACHINE LEARNING

Decentralized machine learning eliminates the requirement for central data aggregation by distributing the training of machine learning models among several devices or nodes. For model training in classical machine learning, data is frequently gathered and delivered to a centralized server. Decentralized machine learning, on the other hand, makes it possible to train models directly on the devices that generate or store the data, protecting privacy, cutting down on communication overhead, and encouraging collaborative learning. Federated learning and edge computing are two essential components of decentralized machine learning. Multiple decentralized devices, each with its own local dataset, work together to train models in federated learning. Each device trains the models locally, and only the model updates—not the raw data—are transmitted to a central server, which compiles them to enhance the global model. Because sensitive data stays on the local device, this method is especially useful in situations where data privacy is an issue.

II. LITERATURE REVIEW

According to Juan C. Olivares-Rojas et al.'s article, as smart meters proliferate in smart grids, new problems in the energy industry have arisen, and applications are constantly being developed to solve them, mostly in the area of data analytics. In smart grid systems, data analytics is typically handled at the server-side layer; however, for optimal performance, data analytics must be processed near the smart meter. Effective data processing also requires the use of approaches that make it easier for data analysis procedures to be integrated into the Advanced Metering Infrastructure (AMI).Based on an edge-fog-cloud computing architecture, this study introduces a novel architecture for data analytics in smart metering systems that supports various forms of data analytics in a multi-tier setting. By employing a reinforcement learning technique, the suggested architecture may learn and adjust to various smart metering system scenarios. Three distinct analytical applications—predicting energy consumption, predicting power quality, and predicting energy theft—were used to test the architecture [1].

According to a report by Ashkan Yousefpour et al., we anticipate a sharp increase in the number of connected devices as the Internet of Things (IoT) becomes more integrated into our surroundings and daily lives. It is anticipated that IoT will link billions of gadgets and people, offering us potential benefits. With this expansion, fog computing and related edge computing paradigms like cloudlet and multi-access edge computing (MEC) are viewed as potential ways to manage the massive amount of time-sensitive and security-critical data generated by the Internet of Things.We begin this study by offering an overview of fog computing and related computing paradigms, highlighting their parallels and distinctions. After that, we offer a taxonomy of fog computing and related computing paradigms. Lastly, we outline the difficulties and potential paths forward for fog computing research. Moving big data from IoT devices to the cloud may not be effective when data velocity and volume rise, or it may even be impossible in certain situations owing to bandwidth limitations [2].





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Guo Mian Recently, edge computing has become a viable addition to cloud computing for quality of service (QoS) provisioning, especially for applications that are sensitive to delays. The quality of the compute experience, such as network transmission latency and transmission energy consumption, could be significantly enhanced by shifting the computationally demanding workloads to edge servers. However, an edge server's computational resources are so limited that they are unable to respond rapidly to the rapidly increasing demands on computing.Queueing delay is therefore unavoidable in computationally demanding environments, such as those with Internet of Things (IoT) applications. Additionally, when workloads are heavy, edge servers may use more compute energy than cloud servers. Collaboration between edge servers and the cloud is crucial for delivering quality of service (QoS) to end users while attaining green computing for computing systems. This research examines the workload allocation problem in an IoT-edge-cloud computing system that is both energy-efficient and delay-guaranteed [3].

In this study, Sudipan Saha et al. have suggested that the development of data is intrinsically linked to the development of artificial intelligence (AI). The majority of industries, however, have data in the form of isolated islands with no opportunity for inter-organizational collaboration. This impedes the advancement of artificial intelligence. In recent years, federated learning has surfaced as a potential remedy for this issue without jeopardizing user privacy. One notable kind of federated learning is federated transfer learning (FTL), which enables knowledge transfer between domains with few overlapping users and characteristics. We offer a thorough analysis of the body of research on this subject in this paper. We examine the history of FTL and its various current uses in greater detail. We also examine FTL from the standpoints of machine learning and privacy. These days, machine learning is crucial to a wide range of applications, such as risk analysis, picture analysis, and commodity selection [4].

In this study, Alejandro Santoyo-Gonzalew et al. have suggested that 5G use cases demand strict specifications like ultra-low latency and ultra-high dependability. Therefore, moving networking, storage, and processing power to the network's edge has become crucial for the implementation of 5G networking. However, if cost effectiveness is to be achieved in this environment, capital and operational costs must be carefully examined; efficiency is directly related to the placement and capacity planning of edge nodes, which are geographically scattered. The Edge Computing nodes placement problem is formulated in this study as a Mixed Integer Linear Programming problem with latency and high-reliability constraints. To address the stated issue, a framework suggestion based on an internal heuristic is presented. The Edge Computing (EC) paradigm has gained significant attention in recent years because to the impending 5G networking revolution and its unparalleled technical demands [5].

III. RELATED WORK

opportunistic Multi-hop routing is used in wireless sensor networks. In this routing method, a node's neighbors listen in on the transmission and create several hops to send information from the source to the destination. The forwarder list contains the collection of neighbor nodes involved in the routing, arranged in priority order. The packet it receives can be forwarded by the node with the highest priority. In order to lower the size of the forwarder list, this study applies Energy Efficient Selective Opportunistic Routing (EESOR), which applies a constraint that the forwarding node is closer to the destination. The suggested EESOR protocol outperforms the current Energy Efficient Opportunistic Routing (EEOR) protocol in terms of average end-to-end delay, maximum end-to-end delay, and network lifetime, according to the NS2 simulator's simulated results.

IV. METHODOLOGY

Similar to the EEOR protocol, the proposed EESOR protocol reduces the size of the forwarder list by imposing the requirement that the forwarder node be closer to the destination. This makes the protocol more efficient. Utilizing acknowledgement packets also improves dependability, because opportunistic routing of the acknowledgement packets balances transmission and reception energy. Reducing the size of the forwarder list and using distinct pathways for data and acknowledgement packets in order to balance energy usage are the main goals of the EESOR protocol. The creation of the routing table and updating it anytime the network changes are the two stages that make up the EESOR protocol's operation.





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4.1 CREATION OF ROUTING TABLE

Every node's routing table is initially created using the data from nearby nodes. The node sends a HELLO packet to each of its neighbors to begin this phase. The HELLO packets are then sent to all of its neighbors using a timer. No specific node receives the HELLO packet. To determine the address of the node that sent the HELLO packet, the receiving node looks at the packet source field.

- 1. Every node has a distinct node identification.
- 2. Every node has a Global Positioning System installed.
- 3. Every node has a distinct node identifier and is aware of its own geographic position.
- 4. The transmission range r is the same for every node.
- 5. Nodes share a single broadcast channel and operate in half duplex.
- 6. DIRCAST's operating MANET is connected
- 7. No two nodes are geographically distinct from one another.
- 8. It is not necessary to be aware of the destinations' locations.

4.2 UPDATING THE ROUTING TABLE

If the nodes are only one hop away, the routing table built in the previous module is adequate for network communication; however, this isn't always the case. The routing table's structure is described in Figure 4.3. Depending on the location of the source, intermediate nodes, and destination, this module updates the entries in the routing table. In order for the next hop node to be the one with the least distance between itself and the target node, the distance between the forwarding node and the target node is updated in the routing table entry. The next hop to a specific destination is determined on the fly and the new protocol is entirely opportunistic, according to the EESOR principle. Until the destination node is reached, this process is repeated. By the end of this module, we will know the shortest route for multi-hop paths in a wireless sensor network from the source to the destination.

4.3 SENDING ACKNOWLEDGEMENT

Transmission Control Protocol (TCP) is the Transport Layer Protocol utilized in this exchange. TCP is a dependable protocol that uses an acknowledgment packet sent from the target to the source node to ensure that every packet reaches its destination. Typically, the acknowledgment packet uses the same intermediate nodes as the data channel but follows the opposite path. By sending the acknowledgment packet opportunistically, the recently adopted Energy Efficient Selective Opportunistic Routing protocol balances the energy used by the nodes for transmission and reception, extending the network's lifespan. The ratio of all data packets received by all destination sides to all data packets transmitted by all source sides is known as the packet delivery ratio. The average network routing load per good data packet is indicated by the ratio of the total number of routing messages (RREQ, RREP, and RRER) to excellent received data packets. The average delay is the sum of the data transmission time, routing delay, and retransmission time for each successfully received packet.





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FIGURE1. SYSTEM FLOW DIAGRAM



I.





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V. RESULT ANALYSIS

When compared to conventional opportunistic routing techniques, the suggested Energy Efficient Selective Opportunistic Routing (EESOR) protocol shows notable gains. The protocol optimizes energy consumption throughout the network and reduces needless transmissions by carefully narrowing the forwarder list to only include nodes closer to the destination. A discernible decrease in end-to-end latency results from prioritizing nodes according to their proximity, which guarantees quicker packet delivery. Moreover, opportunistic routing of acknowledgments effectively balances the energy consumption of transmission and reception tasks, avoiding early node depletion. As a result, the network's overall lifespan is increased as it continues to function for a longer period of time. The evaluation measures unequivocally show that EESOR performs better than current protocols in terms of network sustainability, packet delivery performance, and energy economy.

VI. CONCLUSION

In summary, careful planning, development, and testing efforts lead to a well-executed system implementation. It symbolizes the conversion of abstract ideas into a concrete, useful reality. Delivering a dependable, effective, and user-friendly system that satisfies the requirements is contingent upon the success of this phase. It is critical that development teams collaborate, communicate effectively, and follow best practices for testing and coding.Because it only adds nodes closer to the destination to the forwarder list, the proposed EESOR algorithm is found to decrease the average end-to-end latency and the maximum end-to-end delay lifespan, allowing for a speedy selection regarding the next relay node to be chosen. Because the acknowledgement is also routed opportunistically, it also expands the network and improves packet delivery dependability.

VII. FUTURE WORK

Future research must look into ways to improve the capabilities of the current system and take advantage of new developments in technology. Advanced machine learning algorithms could be the subject of research and development projects in order to improve predictive analytics, automate decision-making, or optimize system performance. The system's efficiency could also be increased by investigating the incorporation of cutting-edge technology like edge computing to lower latency or blockchain for improved security.

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