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An Efficient Mobile Charger Based Scheduling for Design of Mobility-based Algorithms for Wireless Sensor Networks

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Abstract: Mobility in sensor nodes, targets, base stations, or charging vehicles can increase performance in a resource-constrained wireless sensor network (WSN) in terms of the energy economy, minimizing the latency with a longer lifespan, and increasing throughput. It is suggested to use mobile charger scheduling algorithms to recharge the SNs. According to the network scale, single and multiple mobile charger scheduling techniques are suggested in this context. When a new or developing request is received, the charging activity is interrupted when a single MC uses pre-emptive scheduling of the MC. This strategy increases the length of the mobile charger's journey path while maximizing its utility. Unfortunately, a single charger is unable to fulfil the needs of a big network, hence several chargers are required. As a result, multiple mobile charger scheduling for WSNs that is delay-tolerant is also suggested. This clustering algorithm groups the sensors into equal-sized clusters using a new K-medoid structure. The cluster head (CH) is then chosen using the WDWWO (Wind Driven Water Wave Optimization) algorithm, which considers both the distance to the cluster's midway position and the remaining energy. The mobile charger has a WET that may traverse the network either on demand or along a predetermined path to recharge the SNs. One or more chargers are utilized to recharge the SNs depending on the size of the WSNs. To validate the efficacy of the projected strategy, the performance of the projected algorithms is compared to that of a number of already-existing algorithms. From this, we can conclude that our suggested method achieves better charging scheduling to charge the lifetime important sensors than the current works based on the simulation results.

***Keywords**: WSN, SN, MC, CH, WET, WDWWO.*

1. Introduction

In terms of the connectedness and intelligence of different kinds of sensor devices, the IoT (Internet of things) is introducing a new paradigm. Radiofrequency identification (RFID) tags and the broad use of wireless sensor networks have become commonplace because of advancements in semiconductor fabrication technology. Wireless sensor networks, which consider sensor devices as network nodes, are crucial IoT enablers because they allow for the seamless real-time flow of data between sensor nodes, enabling the monitoring, localization, and tracking of objects [1]. The significance of promptly charging the sensor nodes cannot be overstated because the sustainable operation of wireless sensor networks is a key issue, particularly with mission-critical sensor networks. Batteries-powered devices often have short lifespans, and the majority of wireless sensor networks stop working when even a single or small group of sensor nodes run out of energy. Consequently, extending the network lifetime without sacrificing sensing performance is one of the main goals taken into account while constructing a wireless rechargeable sensor network (WRSN) made up of sensor nodes with batteries [2].

WSNs are one of the key technologies for perceiving the physical environment because of their self-organization and ease of deployment. The sensor node possesses the capabilities of processing, sensing, data gathering, data aggregation, and compression coding [3]. In addition to this, the cloud server can send control instructions to the sensor node, which can then be received by the integrated wireless communication module on the sensor node, and the sensor node can then upload data to the cloud server of either the sink node or the base station in real time. Because sensor nodes will process and transfer an overwhelming amount of information over time, the system's energy would steadily deplete, eventually leading to the system's inability to function properly. Because the battery energy cannot be restored once it has been depleted, the sensor nodes will stop functioning,

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which will result in a "hot spot" problem. As a consequence of this, the amount of energy that sensor nodes consume is becoming an increasingly important topic of discussion and is seen as an essential component in the wider implementation of WSNs [4]. In contrast, the condition of sleep will require a far lower amount of energy to maintain than the states of sensing, data receiving, or transmission. The projected scheduling algorithms for sensor nodes aim to increase energy utilisation and, as a result, effectively extend the lifetime of WSN (wireless sensor networks). The vast majority of sensor node batteries are not detachable, and when the nodes' ability to function is compromised due to low battery power, the nodes will eventually stop working. Even if the node sleep scheduling options are more feasible for extending the life of a battery, the problem that was previously noted has not yet been completely overcome [5].

The use of a mobile sink in the methodology helps to alleviate the problem of hotspots and improves data collecting. It is able to support the SNs for a short length of time but cannot do so for an extended period of time [6]. Despite the fact that it distributes energy uniformly throughout the SNs, it cannot. In this regard, the research recommends two techniques for recharging the sensor nodes that are distributed over a network: the first method makes use of a single mobile charger, while the second method makes use of many chargers. The preliminary MCUMPS (Mobile Charger Utility Maximization through Preemptive Scheduling) proposal [7] calls for the use of a single mobile charger in conjunction with a partial scheduling mechanism. This method stipulates that the action of charging a mobile device may be interrupted at any moment. Regrettably, the requirements of a large network cannot be satisfied by a single charger; hence, more chargers are necessary [8].

According to a recent breakthrough in the field of wireless power transmission based on highly coupled magnetic resonances, it is now possible to power a 60W light bulb at a distance of two metres away without the use of wires or plugs, and the wireless power transfer efficiency is estimated to be around 40%. This breakthrough was made possible as a result of the fact that it is now possible to power a light bulb based on highly coupled magnetic resonances. Industry research has brought wireless power transfer efficiency up to 75%, allowing for the transfer of 60W of electricity across a distance of up to two to three feet. This represents a significant improvement over previous levels of efficiency. Commercial goods that are currently available on the market and are based on wireless energy transfer technology include examples such as sensors [9], RFIDs, cell phones, and vehicles. These are only some examples. It is possible for this cutting-edge technology to give sensors the ability to charge at high and stable rates. A recent breakthrough in the creation of ultra-fast charging battery materials [10] provides additional support for the practicability of the wireless power transfer technique. Researchers from MIT devised an ultra-fast charging method for the LiF eP O4 material, which has a charging rate of up to 400 Coulombs per second. As a result, the amount of time necessary to completely charge a battery can be cut down to only a few seconds. In light of this, wireless power charging is a strategy that shows a lot of promise for prolonging the lifetime of WSNs [11].

The outline for the rest of the paper will be presented in the following paragraphs. In part 2, we provide a brief description of the relevant work, and in section 3, we provide a description of the methodology as well as the theoretical foundations of the methods that were employed. In section 4, both the results of the simulation and an analysis of them are presented. In the final section of the chapter, under "major findings," we provide a summary of the most significant findings.

2. Related Previous Work Done

The mobile charger has a WET that may traverse the network either on demand or along a predetermined path to recharge the SNs. One or more chargers are utilized to recharge the SNs depending on the size of the WSNs. A few academics suggested employing deep reinforcement learning (DRL) to develop an effective on-demand charging system for WRSNs. Similar to this, workers employed DRL in other research to deal with the MC arranging in the surroundings. In both situations, the next node to be charged is selected using the effective reward function. These two methods, however, are centralized and have a high level of computing complexity [12]. They evaluated delay-aware scheduling by balancing data collection and energy use [13]. Researchers have suggested a fusion meta-heuristic-grounded MC arranging approach for WRSNs. In order to solve the problem, they combine Cuckoo Search methods with Genetic algorithms. Several researchers have suggested placing static chargers in order to maximize the utility of wireless charging by utilizing an approximation approach. These algorithms, however, need a lot of processing and take a while to procedure the appeal and choose the order [14].

The lengthy path and high computational complexity of this technique, however, are the results. A WSN's dead node count can be reduced effectively by using research conducted by a variety of academicians [15]. This method primarily emphases on the energy loss observation while the other SNs are moving and charging. In their partial scheduling method, researchers charge the SNs in the WRSNs. Even if around of the SNs are not accomplishment their threshold, numerous academics claimed that charging multiple SNs simultaneously is possible in their work [16]. Several MCs were used in a study that projected a cooperative charging approach for WRSN utility maximization. In order to decrease the trajectory of the MCs and maximize utility, they used a path-merging strategy. Several mobile chargers aren't always economical [17].

In this, the early and delayed jobs are used to identify the charging nodes. WRSNs have an effective simultaneous charging approach suggested by a few academics. To determine the accusing time and stallion trajectory for MC efficacy intensification, the authors here suggested a mixed-integer optimization technique [18]. The order of charging must be determined using this approach, which takes additional work. In a study, a multiple MC scheduling approach based on fuzzy logic for rechargeable WSNs is explored. Before scheduling the MCs, academicians split the network in this case. Nevertheless, adding more chargers to a network raises the cost of deployment and maintenance. For both the choice of the SNs' command and the total of energy to be accused during the arranging, a group of researchers offered a task-driven MC scheduling [19-20].

The radiation avoidance of on-demand multi-node energy charging using a number of MCs is discussed in a study. In this research, a novel charging protocol for WRSNs was presented [21]. A few other researchers created an energy-conscious multiple MCs coordination for WRSNs. This article resolves coordination concerns between numerous MCs under various system requirements. This approach aimed to lessen the power depletion of MCs, ensuring that no sensor would run out of power [22]. CCA-NDC (Collaboration Charging Algorithm based on Network Density Clustering) for WRSN was created in this study. A few researchers developed a revolutionary wireless charging algorithm that uses reinforcement learning to charge mobile WSNs (RL) [23]. SNs were given both stationary and portable wireless chargers to represent the article. To develop the charging function in RWSNs, other researchers started supple arranging and charge-oriented sensor node placement. In this article, charge assignments are jointly deliberated upon, and node positions are optimized [24].

Recently, wireless charging methods have been used to produce WRSNs, which can conduct long-term sensing and data-gathering duties. However, in WRSN, effective path scheduling for MWCVs is seen as a fundamental research problem. Two significant WMC issues are optimizing movement trajectory and charging time. Some more research suggested using the WMC technique's route optimization to find the best trajectory, which results in a balanced energy depletion time. With the aid of WRSNs, data-collecting systems are developed to accomplish critical area monitoring [25].

3. Purpose of the Work

1) To develop mobile charger arranging for WSN and design mobility-based algorithms.

4. The Projected Algorithm:

The MCUMPS method is described here. Here, we're primarily concerned with making sure the sink processes requests in a timely manner so that the nodes can be charged. We also determine the STC (Sojourn Time Computation), which is how long the MC will be able to stay in SN. CNs (Crucial nodes), ENs (emerging nodes), and LNs (leaf nodes) are the three types of deployed SNs that the MCUMPS distinguishes (LNs).

It is possible to think of an SN as a Critical Node, denoted by the letter S, in the network. If we take off S, the network could get split up into several segments. Given the potential for network fragmentation in the event of a CN failure, it is imperative that we treat such nodes as critical infrastructure.

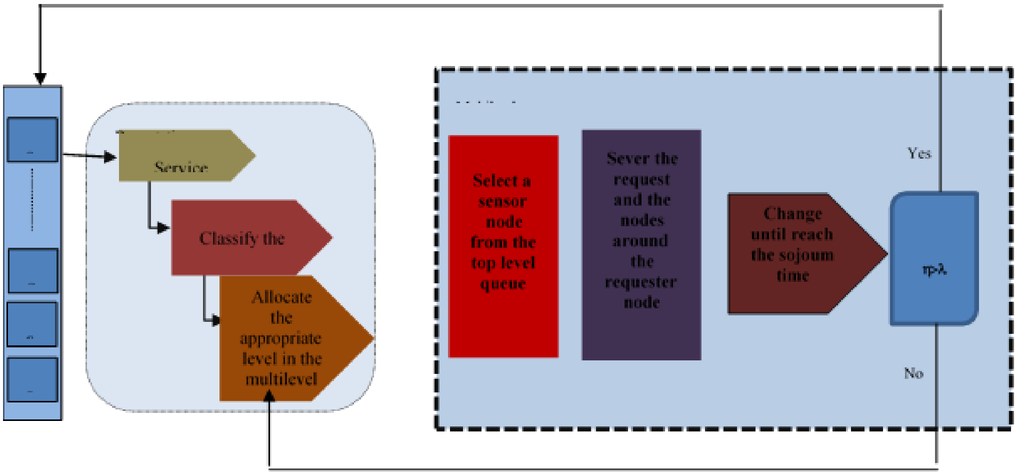

Fig I: The projected MCUMPS algorithm.

Although several nodes link the ENs and SNs together, their loss does not cause the network to split. However, this will change the routing path taken by the other sensor nodes. Misdirection attacks can result from such a shift in strategy. Keeping the ENs powered up is crucial for protecting against diversionary tactics. Consequently, the MC must be scheduled anytime any node in this cluster requires an energy restoration. Nonetheless, it does not pose the same threat as CN trains. Data collection efficiency can be enhanced by carefully selecting ENs to ensure that network energies are balanced. We take into account the SNs with an in degree of 0 as the LNs. Since the leaf nodes have no impact on the network or any other nodes, they are assigned the lowest charging priority. For simplicity's sake, we'll call any nodes that don't fit either the CN or LN categories "entries".

4.1. Sojourn Time Computation: The Sojourn Time is the combined waiting time of all SNs within MC's communication range when the MC is stationed at an SN to recharge. To determine the stay time, just the nodes that were specifically asked about are taken into account, rather than all of the nodes within range of the device's communications. To determine, the STC employs the symbol ω. Using Eq. 1, we can determine the STC of the projected work.

$$STC = \frac{1}{\mu}\sqrt{\frac{1}{|\varphi|}\sum_{i=1}^{|\varphi|}(\omega_i - \mu)^2}$$
(1)

Where, μ is evaluated by equation 2:

$$\mu = \frac{1}{|\varphi|}\sum_{i=1}^{|\varphi|}\omega_i$$
(2)

4.2. K-medoids Clustering Algorithm: Using K-medioids the network's useful life span can be extended and energy costs can be lowered by employing a clustering technique. The concept of universal clustering serves as the foundation for this algorithm. The optimised k-medoids algorithm decreases the number of required iterations by estimating the central circle's mean point and residual energy.

Step 1: Choice of the first medoid: Each pair of nodes should have its distance calculated using the Euclidean metric. Assigning each node to the nearest medoid yields the initial cluster.

Step 2: This step is to update the medoids, which entails finding new medoids for each cluster that have the smallest overall distance to the other nodes in their cluster.

Step 3: Medoids are assigned nodes. Each node is then connected to its neighbouring medoids, yielding a clustering result. The average distance between each node and its medoids is calculated. If the new amount is the same as the old one, then the procedure ends. If not, return to the second step.

4.3. WDWWO algorithm for CH selection: The WDWWO method uses a model of the water's surface waves to discover a prime resolution to the optimization problem. This technique is a hybrid of the WDO (Wind Driven Optimization) and the WWO (Water Wave Optimization) methods. The wave's wavelength grows or shrinks as it travels from deep to shallow water, or vice versa. The problem-solving procedure takes into account three different sorts of operations: propagation, refraction, and breaking. For nodes in deep water, the depth of the ocean or the distance between the seafloor and the surface is taken into account while calculating the residual energy.

WDWWO algorithm:

```
Sensor node array as input
Successfully Optimized CHs
Each of the n waves (sensor nodes) in the population P is set up at random.
in the meantime the cut-off condition is not met
what if x P for all x
Create an x′ by propagating x.
The condition is met if and only if f(x′) > f(x).
then (if f(x′) > f(x))
Split x′ ;
Replace x with x′;
Swap out x for x′;
else
x.h is decreased by one;
Conditional Statement:
Change x to x′ by refraction;
Correct the wavelengths;
end if
end if
end if
conclusion for
cease during
The x that was returned was
```

4.4. Hybrid GFSO (Galactic Sun Flower Optimization) algorithm: In the first step of the hybrid GSFO process, the primary population P is generated at random using the GSO method. Following one round of the GSO algorithm, the optimal answers are saved for future iterations. For better performance of the SFO algorithm, the GSO algorithm can be utilised to find with local search capability. The objective function takes care of the necessity of charging dynamic sensors by using numerous MCs. In this algorithm, the population size and number of iterations begin with the first definition of

GSO and SFO parameters. This algorithm's output should be the maximum value of the fitness function.

5. Result and Discussion:

In this section, we give a thorough simulation experiment-based performance study of Hybrid GSFO and compare it to state-of-the-art systems. Our Hybrid GSFO algorithm is now operational, and it runs on the Java platform. Many measures are used to calculate how much of an improvement in quality the Hybrid GSFO actually offers. Table I lists the simulated parameters used for this charging scheduling procedure. A rectangular area of 600 x 450 metres is used for the simulation, with 100 to 500 sensors spread out across the region in a random and uniform fashion. At the region's epicentre, you'll find the lone BS.

5.1. Energy Reduction: The word "energy reduction" is applied to define the whole expanse of power that is utilized by a network all over the development of sending and receiving data. This value is extremely important for the routing process; but, once clusters begin to form, it also becomes an energy drain.

5.2. Network Lifetime: This subsection assesses the network's expected lifespan in relation to the total network area. Network lifetime is the period that elapses before the first node dies from lack of power. The implemented scheme's energy efficacy can be gauged by its ability to assess the network's lifetime.

5.3. PDR (Packet delivery ratio): PDR is the ratio of packets received to packets sent. The primary success of wireless networks is the transmission of packets. As far as PDR is concerned, this delivery ratio is a success.

$$PDR = \frac{Recieved\ Packet\ Count}{Delivered\ Packet\ Count}$$

(3)

5.4. Packet loss occurs when sent data does not arrive at its intended destination. The network's efficacy and durability are both improved by a decrease in the packet loss rate.

$$PLR = Forwaded\ packet - Recieved\ packet$$

(4)

5.5. End-to-end delay: Reducing Reduced power consumption and increased reliability are two benefits of end-to-end (E2E) delay. Hence, less time spent waiting improves both efficacy and dependability. E2E delay measures how long it takes for a packet to go from one node to another. Time spent on tasks such as data processing, transmission, and reception are all factored into the end-to-end delay.

$$End\ to\ end\ Delay = Time\ for\ (Data\ transmission + Data\ processing + Data\ delivery\ ) \quad (5)$$

5.6. Throughput: The throughput is the rate at which data packets are successfully relayed from the sending node to the receiving node.

$$Throughput = \frac{Forwaded\ data}{Transmission\ time}$$

(6)

Table I: Comparison of existing and projected algorithms concerning different performance metrics by varying the number of sensor nodes between 100 to 500.

Parameters	Nodes Count	Approach	
		FEEC-IIR	Hybrid GSFO
Throughput (kbps)	100	0.91	1.31
	300	0.73	1.18
	500	0.63	1.12
PDR	100	98.14	99.25
	300	97.36	97.45
	500	96.11	96.12
Packet Loss Ratio	100	2.13	0.81
	300	3.24	2.21
	500	5.41	4.32
Energy Depletion (J)	100	52	15
	300	104	26

	500	153	32
End-to-End Delay (sec)	100	2.1	0.1
	300	4.5	1.2
	500	6.3	2.3

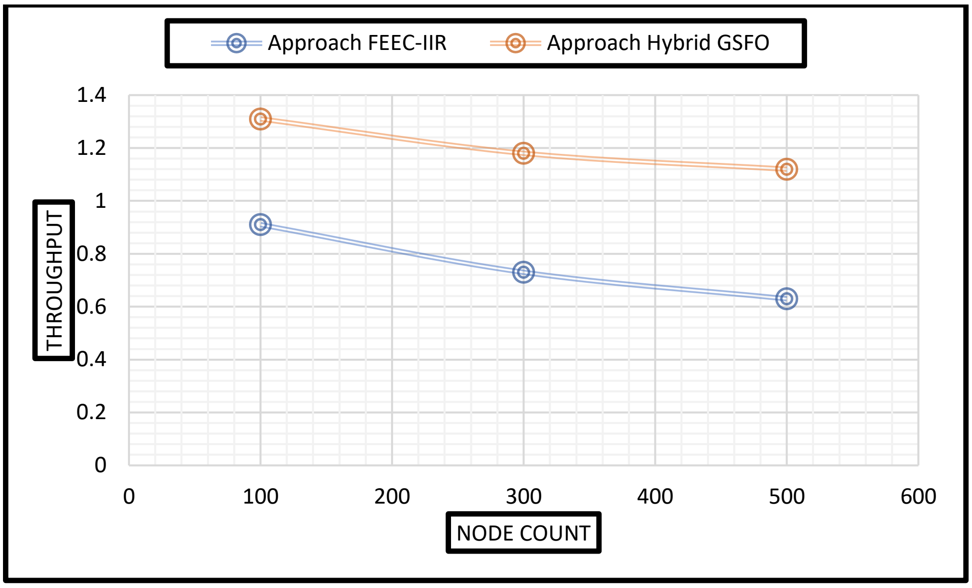

Fig III: Throughput comparison of projected method with existing FEEC-IIR.

Figure III depicts a performance evaluation of throughput. Throughput is more valuable when more nodes are added to the network. Furthermore, it is connected to the currently used methodologies, such as FEEC-IIR approaches. Figure III demonstrates how the suggested hybrid procedure excels over the state-of-the-art methods. Because the suggested approach incorporates optimal power allocation and time management for charging, it is meant to maximise throughput.

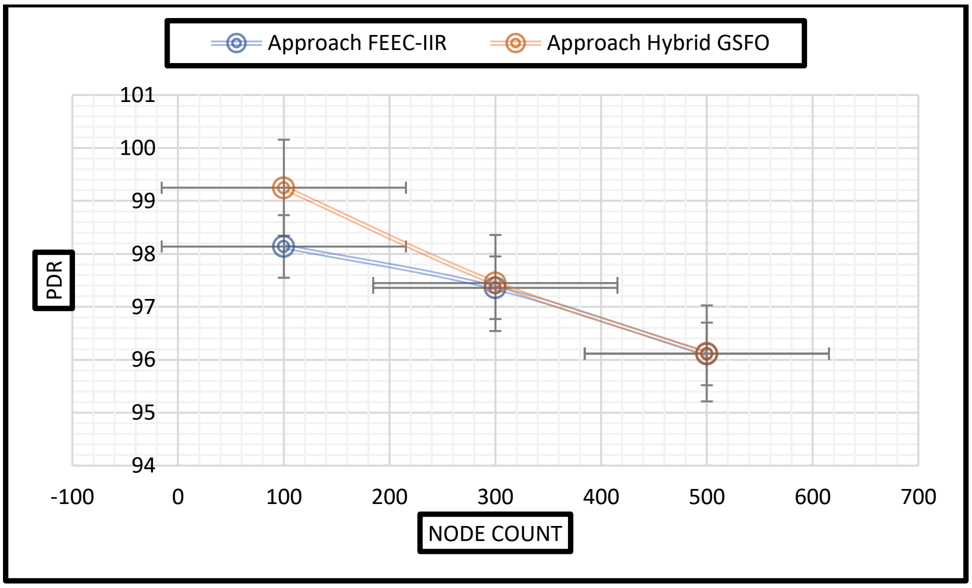

Fig IV: PDR comparison of projected method with existing FEEC-IIR.

Results from the comparison reveal that as the number of SNs increases, the PDR achieved by the suggested technique improves. As a result of the projected hybrid algorithm accurately assigning charging schedules to the MCs, the network will experience zero outages. Hence, the suggested method obtains a greater delivery ratio since data packets can be sent between nodes without restriction as shown in Figure IV.

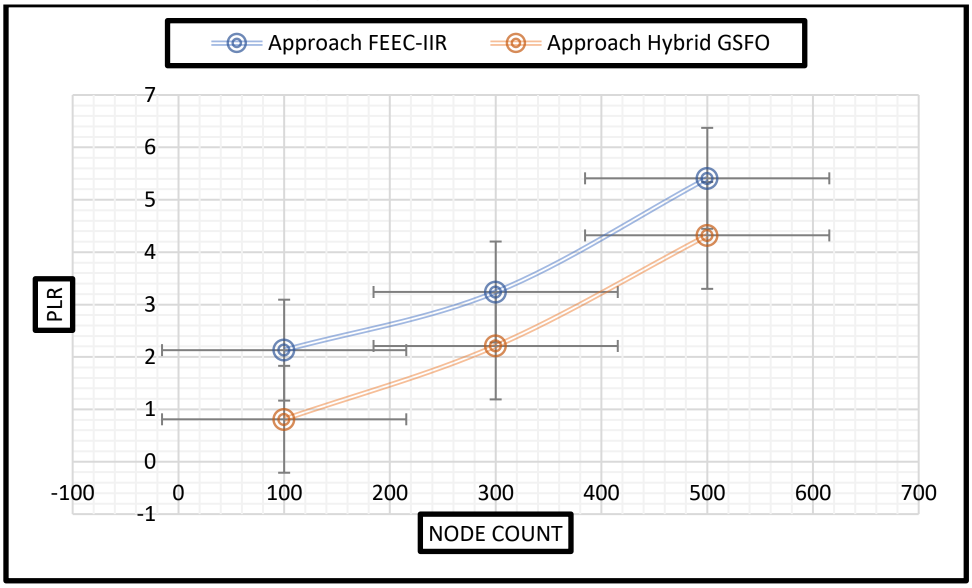

Fig V: PLR comparison of projected method with existing FEEC-IIR.

In Figure V, we see PLR's evaluation in terms of the total number of nodes. The projected technique achieves a lower PLR rate than do current approaches. Reduced packet loss is primarily attributable to the MCs' charging schedules being optimally assigned. Since sensor battery life has little bearing on the transmission of data, and hence less packet loss is experienced when information travels from node to node.

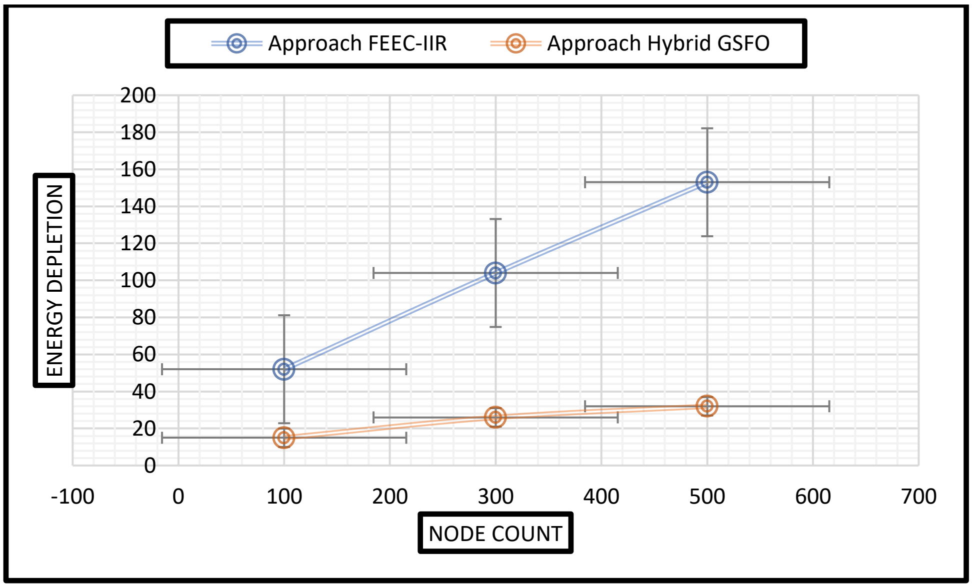

Fig VI: Energy Depletion comparison of projected method with existing FEEC-IIR.

Methods like FEEC-IIR are used as benchmarks for the projected hybrid approach. One hop communication requires sending information from one end to the other, which uses more power. The projected hybrid algorithm utilises the best CH based on the hybrid WDWWO algorithm to transmit data from a specific node to the BS, resulting in a significant reduction in energy consumption compared to conventional approaches as presented in Figure VI.

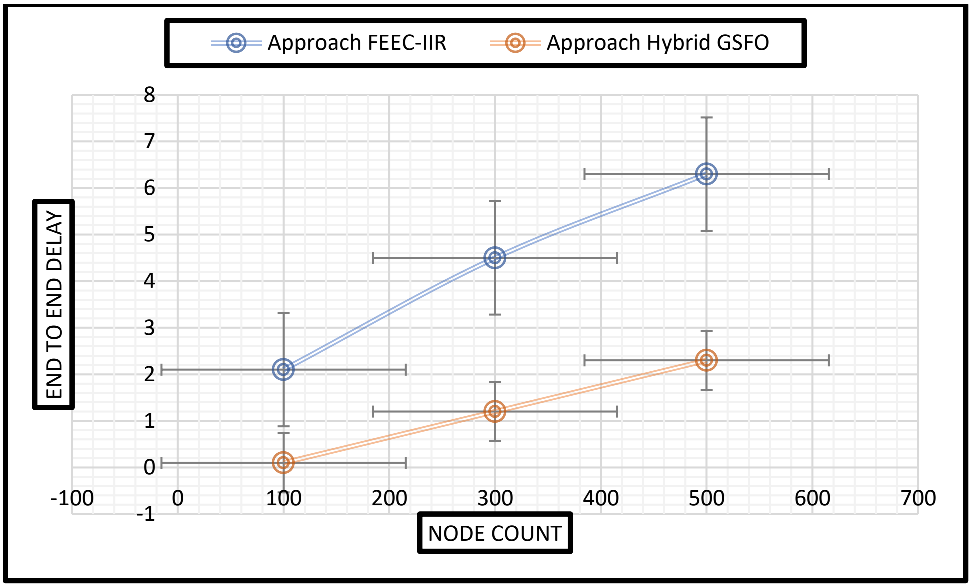

Fig VII: End to End Delay comparison of projected method with existing FEEC-IIR.

Figure VII depicts the E2ED performance calculation in terms of the total number of nodes. The projected method incurs a growing delay as the number of nodes expands. In comparison to conventional approaches, the projected method achieves extremely low delay at 100 nodes. Since the suggested technique reliably transmits data over the CH in the absence of restrictions.

6. Conclusion:

The strategy that makes use of mobile sinks lessens the effect that hotspots have while also improving data collecting. Even while it performs a decent job of distributing power across the SNs, it is not adequate to keep the sensor nodes functioning for a very long time. In this article, we will discuss some of the Hybrid GSFO mobile charger scheduling algorithms that are appropriate for usage with rechargeable WSNs. These algorithms can be found in other related works. The Hybrid GSFO is responsible for coordinating the use of a large number of mobile chargers while taking into consideration the recharging cycles of each sensor in the network. After the K-medoids clustering has been completed with the help of the Hybrid GSFO, the WDWWO method is used to select the ideal cluster head from each cluster. This method takes into account both distance and residual energy. In conclusion, a hybrid version of the GSFO algorithm is presented here as a potential answer to the problem of charging schedules for multiple chargers. The goal of hybrid GSFO approaches is to cut down on the total number of nodes in a network that fail at some point. In order to demonstrate that the projected technique is effective, the performance of the algorithms that are projected is compared to the performance of a number of algorithms that are already in existence. Because of this, we are able to draw the conclusion that the way that we have provided produces better charging schedule to charge the lifetime essential sensors than the current method that is being used, which is based on the simulation findings.

Conflict of Interests:

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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