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RESEARCH ARTICLE

Enhanced Intelligent Water Drop Algorithm Optimized Routing (EIWDR) for Quality of Service Enhancement in Internet of Things-Based Wireless Sensor Networks (IWSN)

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Abstract – The Internet of Things (IoT) has transformed how humans engage with technology, allowing pervasive connection and data sharing. In the Wireless Sensor Networks (WSNs) framework, IoT-based applications have been created for several areas, including agriculture, where greenhouse automation has been deployed for enhanced agricultural yields. However, WSNs face significant challenges, such as limited resources, unpredictable communication, and energy consumption. These issues become more pronounced when applied to greenhouse agriculture due to interference, congestion, and quality of service (QoS) requirements. Therefore, efficient routing protocols are crucial to address these challenges. The proposed study addresses the routing issues in IoT-based WSNs (IWSN) for greenhouse agriculture. Specifically, the Enhanced Intelligent Water Drop Algorithm Optimized Routing (EIWDR) is proposed as a novel routing protocol to enhance the QoS in IoT-based WSNs. The EIWDR protocol utilizes the intelligent water drop algorithm to optimize the routing path selection. The algorithm prioritizes energy-efficient routing, selects the most reliable path with minimum delay and data loss, and balances network load to prevent congestion. The proposed protocol also uses a modified weight function to improve the routing performance when applied in IWSN. To test the efficacy of the EIWDR, simulation tests were conducted in the NS-3 simulator. The EIWDR protocol fares better regarding network lifetime, packet delivery ratio, energy consumption, and packet delay than other routing protocols. Improved greenhouse agricultural quality of service using IWSN is possible with the help of the proposed EIWDR protocol. With the help of intelligent routing algorithms, network resources are used effectively, data is sent reliably, and overall performance is enhanced.

Index Terms – IoT, WSN, Routing, Greenhouse, Agriculture, QoS.

1. INTRODUCTION

With rising food costs and a growing population, technological advancements in agriculture have taken on greater significance in recent years [1]. Greenhouse farming is one example of how technology has improved farming practices. Improvements in greenhouse farming are increasingly being sought through the application of the Internet of Things (IoT) and Wireless Sensor Networks (WSN) [2]. Many crops may be grown in greenhouses yearly, pests and diseases can be managed, and water and fertilizer management is enhanced [3]. Yet, it does not come without difficulties, such as regulating environmental factors like temperature, humidity, and light to guarantee the best agricultural yields. Here’s where the IoT-based WSN (IWSN) comes in [4].

Embedded with electronics, software, sensors, and network connection, the IoT enables physical items, cars, and other things to gather and share data [5]. The sensors in a WSN are compact and have a low power consumption; they are used to keep tabs on things like the surrounding temperature, humidity, and light levels. After collecting data, these sensors can send it to a gateway that can be processed and utilized to make choices [6].

IWSN can be used in greenhouse agriculture to monitor and regulate the environment and track the development and health of crops [7]. Temperature, humidity, light intensity, and soil moisture levels are just some variables that sensors may monitor and control. As a result, plant development may be optimized, and the danger of disease and pests is diminished [8].

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1.1. Routing

The routing protocol of an IWSN is what decides how the sensors' data gets to the network's hub or gateway. The effectiveness and efficiency of a network are very sensitive to the routing protocol in use. Due to the unique needs of greenhouse agriculture, standard routing protocols like AODV and DSR may not apply to IWSNs. As a result, there is a requirement for more developed routing protocols tailored for WSN applications in greenhouse agriculture.

By maximizing efficiency and decreasing latency, improved routing protocols can boost the functionality of IWSN in greenhouse agriculture. For instance, a Minimal Cost Routing (MCR) protocol can optimize energy efficiency by choosing the path with the lowest energy cost for the network. Conversely, a Delay-Aware Routing (DAR) protocol can lessen delays in data transfer by opting for the least-delayed option.

Increased output, efficiency, and longevity are all possible with the help of IWSN in greenhouse agriculture. Sensors and other Internet of Things devices enable farmers to keep tabs on their crops in real-time, fine-tuning environmental conditions for maximum yield with little waste. Improved routing protocols can also help IWSN function better in greenhouse agriculture by minimizing the time it consumes for sensed data to be sent and the energy it consumes. Hence, using IWSN in greenhouse agriculture can be a potential answer to the dual challenges of meeting the rising need for food production and maintaining environmentally responsible agricultural methods.

1.2. Quality of Service

Quality of Service (QoS) is a critical requirement for IWSNs that use routing protocols to transmit traffic flows. Routing protocols in IWSNs should provide a certain level of QoS for packet loss, throughput, and delay [9]. The QoS requirements in IWSNs vary depending on the application and the data transmitted type. For instance, a surveillance application might require low latency and high throughput, while a monitoring application might require low power consumption and low packet loss [10].

To ensure QoS, routing protocols in IWSNs should consider the following factors [11–13]:

- Traffic Type: The QoS standards vary depending on the nature of the traffic flow. Data gathering, for example, may tolerate larger latency and packet loss than real-time traffic like video or speech, which demands minimal delay and fast throughput.
- Network Topology: The network topology is critical in determining the QoS requirements. A hierarchical network topology might require more delay but less packet loss, while a mesh network topology might require a lower delay and higher throughput.
- Node Capacity: The capacity of the sensor nodes plays a critical role in determining the QoS requirements. Nodes with higher processing power and memory can handle more traffic flows and provide better QoS.
- Energy Efficiency: QoS requirements in IWSNs should also consider energy efficiency. Routing protocols that consume less energy can provide a longer network lifetime and better QoS.

To provide QoS in IWSNs, routing protocols use various scheduling, prioritization, and congestion control techniques. These techniques help manage network resources and meet QoS requirements [14]. For instance, Scheduling techniques might prioritize real-time data transmissions above other types of traffic. In contrast, networks that employ congestion management algorithms experience far less packet loss and congestion.

QoS in IWSNs may be greatly enhanced by employing QoS-aware routing techniques. [15]. QoS-aware routing protocols involve adding QoS-awareness to existing routing protocols. This approach can ensure that the QoS requirements of different traffic flows are met, providing a better user experience and enhancing the network's performance [16].

QoS is a critical requirement for WSNs, and routing protocols are crucial in ensuring QoS for different types of traffic flows [8]. Routing protocols should consider various factors such as traffic type, network topology, node capacity, and energy efficiency while providing QoS. Using QoS-aware routing protocols and various scheduling, prioritization, and congestion control techniques can significantly improve QoS in IWSNs, providing a better user experience and enhancing the network's performance [17].

1.3. Problem Statement

The IWSN have been widely used for greenhouse automation to improve crop yields. However, the limited resources, unpredictable communication, and energy consumption of WSNs present significant challenges for achieving QoS requirements in IoT-based WSNs for greenhouse agriculture. The existing routing protocols do not efficiently address these challenges.

Therefore, there is a need for a novel routing protocol that can optimize routing paths for improved QoS in IoT-based WSNs for greenhouse agriculture. The problem statement is to propose and evaluate a novel routing protocol that can enhance the QoS of IoT-based WSNs for greenhouse agriculture by addressing energy efficiency, reliability, load balancing, and congestion control issues.

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1.4. Objective

The main intention of this study is to design and develop a unique routing protocol called Enhanced Intelligent Water Drop Algorithm Optimized Routing (EIWDR) to improve the QoS of IWSN used in greenhouse farming. To boost IWSN network performance in terms of lifetime, packet delivery ratio, and energy consumption, the EIWDR will attempt to accomplish congestion management, load balancing, and reliable data transmission via energy-efficient routing. To prove the superiority of the EIWDR protocol in improving the QoS of IWSN for greenhouse agriculture, this research will conduct simulation tests using the NS-3 simulator to measure the efficacy of the proposed protocol.

1.5. Organization of the Paper

The paper begins with an introduction (Section 1) that provides an overview of the research topic, including routing and quality of service in the Internet of Things-based Wireless Sensor Networks (IWSN). The problem statement and objectives are clearly defined. The literature review section (Section 2) explores existing research and related studies. The subsequent sections (Section 3) focus on the proposed Enhanced Intelligent Water Drop Algorithm Optimized Routing (EIWDR) and its components, such as EEIWDR for IWSN, Local Search Optimizer (LSO), and Pheromone Concentration, as well as the fusion of EIWSDR in IWSN. The paper also includes a section about the simulator used for the research (Section 4), performance metrics used to evaluate the proposed solution (Section 5), and the results and discussion section (Section 6) to present and analyze the findings. Finally, the conclusion (Section 7) summarizes the key points and highlights the research contributions and potential future directions.

2. LITERATURE REVIEW

"Software-Defined Network-Based Energy-Aware Routing" [18] is proposed for minimizing the energy needs in Industry 4.0. Using data collected in real-time from the sensor nodes' energy usage, software-defined networking (SDN) is used to distribute network resources and improve routing pathways dynamically. By dynamically adjusting the routing pathways, it can achieve a power-consumption equilibrium among the sensor nodes. This is accomplished by dividing the network into smaller subnetworks, or "clusters," and assigning a leader, or "cluster head," to each cluster. The cluster leaders gather information about the cluster's energy use and provide it to the SDN controller for processing and decision-making. After analyzing the data on energy use, the controller comes up with the best routes and sends them back to the cluster leaders. "Multi-Path Routing Algorithm" [19] is designed to increase network uptime and decrease energy consumption. It considers the WSN and decides which pathways to use for data transmission. Path weights are calculated using semi-supervised learning methods and are kept up-to-date using information gathered from the sensor nodes. Sending data via several pathways makes networks more resilient to problems like node outages and congestion. It excels in large-scale sensor networks since that's where problems like node failure and congestion are most likely to arise.

"Optimized Hybrid Routing Protocol" [20] aims to minimize energy consumption and prioritize the selection of cluster heads. It combines centralized and distributed methods to pick cluster heads with enough energy and spread the data transmission task among the nodes in an effective manner. It partitions the system into smaller groups called clusters to facilitate between WSN and its nodes. The cluster's strongest and most communicative nodes are selected as cluster heads. The cluster leaders then distribute the data transmission demand across the cluster nodes. By optimizing cluster head selection and data transmission job allocation, the protocol may reduce variance in power consumption across sensor nodes, allowing the network to operate for a longer period. "Energy Efficient Clustering Routing Protocol" [21] is suggested as a clustering routing protocol for WSN that uses a unique admission allotment system (AAS) to improve communication between intra-clusters while conserving energy. It chooses cluster heads centrally, considering their remaining energy and connections to other nodes. The AAS is then used to dynamically assign resources for data transmission across nodes within each cluster. The protocol can reduce the sensor nodes' power consumption while ensuring reliable data transmission by improving intra-cluster communication through the AAS. The protocol may also adjust to new conditions in the network, including the loss of nodes or a shift in the way traffic is distributed.

"Hybrid Secure AOMDV" [22] is intended to deal with the power, computational, and communication constraints plaguing WSNs and threatening network security and performance. The data packets are encrypted with a symmetric key encryption method, so only authorized nodes may decrypt them. In addition, it employs a refined version of the Salp Swarm Algorithm to boost the network's efficiency further. The oceanic behaviour of salps inspired the development of the Salp Swarm Algorithm, a metaheuristic optimization method. The method aims to find the best possible pathways through the network between nodes. Bio-inspired Optimization [23–25]can also be applied in networking for better results.

"Simultaneous Optimization" [26] presents a two-tiered evolutionary approach for improving WSN's inter-cluster routing and cluster head selection. The network's efficiency and power consumption heavily depend on the choices made while picking cluster heads and routing between them. The 2-stage genetic algorithm consists of two phases of operation. The algorithm chooses cluster leaders according to their

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connection, energy, and proximity to other nodes. Using a fitness function, the algorithm scores cluster head candidates on their residual energy, connection, and proximity to the home base. After that, the genetic algorithm chooses the most suited cluster leaders. Fusing the ant colony optimization with the genetic algorithm finds the best routes between clusters. The distance between each cluster, the quantity of excess energy, and the number of hops all contribute to the fitness function's ranking of feasible routes. The computer then chooses the action that will maximize fitness gains.

By fusing the K-means clustering method with the diffusion-based approach, the "Hybrid Diffusion Clustering Scheme" [27] solves the most pressing problems in WSN. The K-means method is utilized as a starting point when first grouping nodes together. The clusters are then refined using a diffusion-based technique to deal with nodes of varying energies. The energy is redistributed among the nodes via a diffusion process in the diffusion-based algorithm, which guarantees uniform consumption across the network. A mechanism is built to tailor the node's transmission radius to its energy output. Higher-powered nodes are allotted a wider transmission range, allowing them to reach further away from one another while maintaining low communication costs. It also specifies how each cluster's leader is selected as a conduit for data from the other nodes to the central hub. The amount of energy available plays a role in determining which node in a cluster will serve as its leader.

"Novel Routing Algorithm" [28] estimates link quality using Bernoulli sampling, which refers to the dependability and quality of the communication connection between two network nodes. More specifically, every node regularly sends a broadcast message to its neighbours, and the receivers validate the message using a probabilistic threshold. The number of successful transmissions is then used to determine the link quality, and the routing path is modified appropriately. Energy use, distance travelled, and available battery life are also considered while determining the best routing method. "Energy Efficient Distributed Routing" [29] divides the routing responsibility among several nodes, hoping to reduce the WNSNs' overall power usage. The three primary parts are the cluster creation process, the distributed routing system, and the load-balancing technique. Based on the nodes' energies and locations, the network is divided into smaller subnetworks or clusters. The load-balancing mechanism shifts the burden amongst the network's nodes to conserve power and make the most of available resources. It reduces the amount of data transferred by simultaneously sending many packets of information.

"Ellipse-Guided Routing Algorithm" [30] is a strategy for making WSNs more effective in energy consumption and network coverage. The method accomplishes its task by segmenting the network into sections. The positions of the nodes define the same and then fit an ellipse to each of those parts. An algorithm considers the ellipses' orientation and location when deciding which path to take when sending a data packet from node to node. It weighs factors, including battery life, travel time, and energy efficiency, to determine the best route. The program uses an ellipse-guided technique to guarantee that data packets are sent along the most efficient path, which enhances network coverage and decreases power consumption. This technique can potentially boost WSNs' functionality and productivity greatly.

"Segmented Sectors in Energy Efficient Routing (SSEER)" [31] partitions the network into many smaller "sectors," into which individual nodes are placed according to their physical locations. To optimize traffic flow, we further subdivide each sector into sub-sectors. In a multi-hop communication setup, data packets go from a sending node to a receiving node through a series of intermediate nodes. Several criteria, including remaining node energy, destination distance, and network quality, determine which nodes will be intermediates. The cluster heads are the gatekeepers between the sectors and transmit data packets between them. Several criteria, including remaining energy, location, and connectivity to other clusters, are used to choose which nodes will serve as cluster chiefs.

"Cluster Routing Protocol (CRP)" [32] aims to improve these networks' energy efficiency, reliability, and data transmission coverage while utilizing the latest advances in fog computing and 5G technology. It uses a hierarchical clustering approach, splitting the network into multiple subnetworks led by different individuals (CH). The CHs connect the WSN to the fog computing layer and play an intermediary role there. It uses 5G and fog computing's most recent developments to make data transfer more secure and widespread. The protocol uses a fog-enabled network architecture, wherein the WSN receives additional processing power and storage space from the fog computing layer.

3. ENHANCED INTELLIGENT WATER DROP ALGORITHM OPTIMIZED ROUTING (EIWDR)

The EIWDR method has a fast convergence rate in solving routing issues in IWSN and can conduct global searches. General routing protocols become stuck in local optima if not given enough time to fully explore the search space and find better solutions (i.e., routes). Hence, the EIWDR algorithm incorporates a local search strategy into a global search optimizer for a better solution. EIWDR explores the feasibility of incorporating a local search optimizer into the EIWDR.

3.1. EEIWDR for IWSN

The EIWDR method has been modified to accommodate peculiarities present in IWSN. The primary adaptation involves ensuring the feasibility of the EIWDR searches

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through saturation degree. This element has been integrated into the customized EIWDR algorithm. The customized EIWDR algorithm for IWSN comprises six primary phases, each involving multiple steps. These phases and steps are designed to make the Adapted EIWDR algorithm functional for IWSN.

3.1.1. Initialization of Static Parameters

The initialization of static parameters is a crucial step in using the EIWDR. These parameters remain constant throughout the search process and include variables that do not change.

- sf_{max}: The maximum iterations allowed.
- Declines: The number of connected water droplets $(p_1, p_2, \ldots, p_{Drops})$ that represent the number of routes available.
- d_{val}, v_{val} and u_{val}: The velocity update function is controlled by a collection of parameters called velocity updating parameters.
- d_{soil}, v_{soil} and u_{soil}: A collection of soil updating parameters that control the soil update function.
- InitialSoil: This is the baseline for the soil specimen and the dirt along route s and t_h. Its values are set using the formula $IWDsoi(s, t_h) = InitialSoil$.
- $\varphi IWD_e, e\ \omega\ \{1,2, \ldots, Drops\}$: The parameter for updating soil globally might vary from 0 to 1.

Input:

1. Parameters
2. Number of drops
3. Maximum number of iterations
4. Evaporation rate
5. Initial random solution generation

Output:

1. Best solution found during the iterations.

Procedure:

For each iteration

1. Calculate the cost function of each water drop solution.
2. Determine the best solution among all the water drops.
3. Update the pheromone trail of each water drop based on its solution quality and the evaporation rate.
4. Generate new solutions for each water drop based on the updated pheromone trail and a local search procedure.
5. Repeat steps (a) to (d) until the maximum number of iterations is reached.

Algorithm 1 Intelligent Water Drop Algorithm

Algorithm 1 provides the core pseudocode of the Intelligent Water Drop Algorithm.

3.1.2. Initialization of Dynamic Parameters

The route construction process initializes parameters at the outset and updates them dynamically. These settings are returned to their default values at the beginning of each loop. Some of the significant dynamic parameters are:

- $R_e(EIWDR)$: Routes that are selected using the solution $EIWDR_e$, wherein $e\ \omega\ \{1,2, \ldots, Drops\}$.
- $InitialVel$: The solution's initial velocity is $EIWDR_e$.
- $EIWDRsoil_{r_{EIWDR}}$: The first soil that was loaded into solution $EIWDR_e$.
- F^{zv}: The EIWDR algorithm resets the locally optimal solution after each iteration. The solutions found during those iterations with the lowest penalty value are denoted by F^{zv}.
- F^{Fv}: The global best solution is the population's least penalized routing strategy. Each time the EIWDR algorithm iterates and this solution is likewise synchronized.

3.1.3. Distribution of Random Timeslot

During the Adapted EIWDR phase, a random data transmission time is selected and assigned a random timeslot to each node as per the procedures given in Algorithm 2. This is done for e belonging to the set $e\ \omega\ \{1,2, \ldots, Drops\}$. Additionally, details of each node visiting are included in e, and it is updated in $R_e(IWD)$.

Step 1: Set $e = 0$

Step 2: $e < Drops$ do

Step 3: Rnd route = Choose a route at random.

Step 4: RndTslot = Tslot picked at random from the available ones.

Step 5: Give $EIWDR_e(rndroute)$

Step 6: Refresh the history of tested routes $R_e(EIWDR)$.

Step 7: Put a e on the counter.

Step 8: Finish while

Algorithm 2 Distribution of Random Timeslot

3.1.4. Route Construction

During route construction, EIWDR identifies different routes using the updated $R_e(EIWDR)$. Choosing a viable component

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that does not break any hard constraints of the routing issue is an additional route at each level of route construction. Each route is identified in a time slot in the outer loop, and in the inner loop route is constructed based on saturation level (SL). When the entire population's uncertain requirements are met, the route construction will end after the threshold number of solutions has passed through the graph. The route construction process comprises the subsequent steps:

The SL principle is employed in this step to determine which route t_h should be used in the solution $EIWDR_e$ for sending the data. Thereby making it the key adaptation of the EIWDR.

Maintaining route constructability in SL requires the utilization of the $EIWDR\_route\_Tslot\ (Drops, C, M)$ matrix. For example, consider the $EIWDR\_route\_Tslot\ (Drops, C, M)$ binary matrix represented in Eq.(1).

$$EIWDR_{Exam_{Tslot(e,h,m)}} = \{1,\ If\ route\ can\ be\ feasibly\ scheduled\ in\ timeslot\ m\ 0,\ Otherwise \quad (1)$$

In Eq.(1), $e\ \omega\ \{1,2,\ldots.,Drops\}, h\ \omega\ \{1,2,\ldots.,C\}$ and $m\ \omega\ \{1,2,\ldots.,m\}$. In EIWDR, $EIWDR\_route\_Tslot(e,h,m)$ plays a crucial role in selecting the next route t_h to be scheduled for utilization. All elements of $EIWDR\_route\_Tslot(e,h,m)$ are initialized to 1 and updated based on the conflict matrix. The SL uses Eq.(2), $EIWDR\_route\_Tslot(e,h,m)$, to find the route t_h that requires the minimal possible time slots.

$$t_h(e) = arg_{h\omega[1,C]} \sum_{m=1}^{m} EIWDR\_route\_Tslot(e,h,m)$$

$$m\ \omega\ \{1,2,\ldots.,Drops\} \quad (2)$$

Route t_f is the next route to be utilized after the route $t_h(e)$ in the solution $EIWDR_e$ is utilized. It has the fewest possible timeslots. After determining, if the value of $EIWDR\_route\_Tslot(e,h,m)$ equals 1 where $M\ \omega\ \{1,2,\ldots.,Drops\}$, the matrix $EIWDR\_route\_Tslot(e,h,m)$ is used to allocate a timeslot β to the route t_f. If the number is 1, it is a good time to schedule the route utilization.

EIWDR uses a probability function to choose a route from various timeslots when the minimum possible time slots are equal. Eq.(3) determines this function the same.

$$\varphi EIWDR_e(t_h) = \frac{g(EIWDRsoil(s,t_h))}{\sum_{f\notin Ru(EIWDR)}^{n}(EIWDRsoil(s,m))g} \quad (3)$$

$EIWDRsoil(s,t_h)$ is computed using Eq.(4) and Eq.(5).

$$g(EIWDRsoil(s,t_h)) = \frac{1}{\varrho_e + j(EIWDRsoil(s,t_h))} \quad (4)$$

Consequently

$$g(EIWDRsoil(s,t_h)) = \{EIWDRsoil(s,t_f)(EIWDRsoil(s,z) \geq 0)\ EIWDRsoil(s,t_f)(EIWDRsoil(s,z))Otherwise \quad (5)$$

The route t_f is part of a vector that consists of elements from the set $S\ \omega\ \{Z_1, Z_2, \ldots., Z_a\}$. The value of a is the maximum number of routes that can be held simultaneously on a single iteration. After choosing the next route t_f to be added to the visited-route array $R_w(EIWDR)$, it assigns t_f it to a possible time slot β. This means that route t_f, which has the minimum number of timeslots in the solution EIWDRs, is assigned to the feasible timeslot β according to Algorithm 3.

Step 1: Foreach $(f = 0\ to\ M)$

Step 2: If $EIWDR\_route\_Tslot(e, t_f, f) = 1$

Step 3: Inject Tslot f into τ Vector.

Step 4: Endif

Step 5: End Foreach

Step 6: β = Choose at random from the digits τ.

Algorithm 3 Route Scheduling at Random Time β in Format t_f.

Route t_f and the conflict matrix will be used to revise the $EIWDR\_route\_Tslot(e,h,m)$. Routes that clash with t_f $(i.e. \alpha\ \omega\ \{h_1, h_2, \ldots., h_b\})$ will have their associated timeslot 5 set to 0 if route 5 in $EIWDR_e$ is scheduled for timeslot 3.

$$\sum_{s=1}^{b} IWD_{Exam_{Tslot(5,s,1)}} = 0\ h_s\ \omega\ \alpha \quad (6)$$

When constructing the solutions $EIWDR_e$ route by route, if it is not feasible to achieve the desired outcome for $EIWDR_e$, to fix the feasibility problem, the route reconstruction procedure will begin. The velocity $EIWDR_e(velocity^{IWDe}(f+1))$ is updated each time a route utilization is moved from s to t_f using the following Eq.(7).

$$velocity^{IWDe}(f+1) = velocity^{IWDe}(f) + \left(\frac{d_{vel}}{v_{vel} + u_{vel} \times IWDsoil^2(s,t_f)}\right) \quad (7)$$

The $velocity_{EIWDR_e}(f+1)$ indicates the speed of the revised timeline $EIWDR_e$. The static parameters determine it. $d_{vel} = 2$ and $v_{vel} = 0.01$, which accounts for the non-linear relationship between the solution's velocity e and the converse of the soil volume along the regional route (represented by $EIWDRsoil(s,t_f)$. The next route is being constructed in the route solution e, both $EIWDRsoil^{EIWDRe}$ and $EIWDRsoil(s,t_f)$ are updated using Eq.(8) and Eq.(9).

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$$EIWDRsoil(s,t_f) = (1-\varphi) \times EIWDRsoil(s,t_f) - \varphi \times \Delta EIWDRsoil(s,t_f) \quad (8)$$

$$EIWDRsoil^{IWDe} = EIWDRsoil^{IWDe} - \Delta EIWDRsoil(s,t_f) \quad (9)$$

The value φ is a positive constant that falls from zero to one. The quantity $\Delta EIWDRsoil(s,t_f)$ represents the amount of soil eliminated from the local path and transferred by a solution e. It should be noted that $\Delta EIWDRsoil(s,t_f)$ is proportional to the inverse of $velocity_{EIWDR_e}(f+1)$ in a non-linear manner, represented in Eq.(10).

$$\Delta EIWDRsoil(s,t_f) = \frac{d_{soil}}{v_{soil}+u_{soil}\times time\left(s,t_f;velocity_{EIWDR_e}(f+1)\right)} \quad (10)$$

The static parameters $d_{soil}, v_{soil}, u_{soil}$ are utilized to represent the non-linear correlation between $\Delta EIWDRsoil(s,t_f)$ and the inverse of $velocity_{EIWDR_e}(f+1)$. It is important to note that $time\left(s,t_f;velocity_{EIWDR_e}(f+1)\right)$ represents the duration required for the timetable solution e to shift from exam s to exam t_f at $timeslot(f+1)$ and it is represented in Eq.(11).

$$time\left(s,t_f;\ velocity_{EIWDR_e}(f+1)\right) = \frac{HUD(t_f)}{velocity_{EIWDR_e}(f+1)} \quad (11)$$

The degree of heuristic desire at the border between test s and t_f is $HUD(t_f)$. As a $g(EIWDR_e)$ following the subsequent test t_f is scheduled, we utilized $HUD(t_f)$. Keep in mind that the penalty amount for the partially built. $EIWDR_e$ may be estimated using the heuristic $HUD(t_f)$ of $EIWDR_e$.

Choosing which routes to explore, modifying the velocity, and updating the local soil is repeated until the stopping conditions for achieving a comprehensive solution are met.

3.1.5. Improving Existing Solutions

Once the $EIWDR_e$ are generated in the fourth phase, the phase of solution improvement is initiated. The best local solution is designated as F^{zv}, is chosen for each $EIWDR_e$ based on the Eq.(12).

$$F^{zv} = arg\left(g(IWD_e)\right) \quad (12)$$

The $EIWDR$ solution's improvement phase finds the local best solution, given by the notation F^{zv}, for each $EIWDR_e$. The objective function $g(EIWDR_e)$ is used to rank the schedule solutions in terms of quality. To fortify water droplets across consecutive iterations, the global soil update equation is applied to all edges between the present route s and the next route t_f in F^{zv}. The goal of these iterations is to find the optimal solution, and it is expressed in Eq.(13).

Eq.(13) involves a positive constant $\varphi EIWDR_e$ and a process of iteration where the best solution, represented by F^{Fv}, is either replaced by F^{zv} or kept the same. This is done during each iteration, and Eq.(14) expresses the same.

$$IWDsoil(s,t_f) = (1+\varphi IWD_e) \times IWDsoil(s,t_f) - \varphi IWD_e \times \frac{1}{H_{F^{Fv}}} \times IWDsoil_{Fv} IWD_e \quad \forall (s,w)\omega\ F^{Fv} \quad (13)$$

$$F^{Fv} = \{F^{zb}, Iff(F^{zb}) \leq g(F^{Fb})\ F^{Fv},\ \ Otherwise \quad (14)$$

The primary goal of the method is to locate the best global solution, F^{Fv}, which is the solution with the lowest penalty throughout all possible iterations. The local best solution, on the other hand, is denoted by the notation F^{zv} And stands for the optimal result of each iteration. The $EIWDR$ checks the value of the local best solution F^{zv} to the value of the best global solution F^{Fv} for all solutions F^{IWD_e} to determine the best global solution F^{Fv}. When the best global solution F^{Fv} is less than the best local solution F^{zv}. EIWDR utilizes the best global solution F^{Fv}.

3.1.6. Termination

Solutions construction and enhancement phases are repeated until a termination condition is reached.

3.2. Local Search Optimizer (LSO)

EIWDR is a meta-heuristic optimization-based routing that can solve various routing issues in IWSN. Local search is an important aspect of the EIWDR algorithm that can be used to improve the quality of the solutions obtained by the algorithm. Local search is a heuristic method that aims to improve the quality of a given solution by iteratively exploring the neighbourhood of the solution and making small changes to it. In the context of the EIWD algorithm, local search can refine the solutions obtained by exploring the solutions' neighbourhoods and making small adjustments to the routes.

To implement local search in the EIWDR algorithm, the following steps are followed (Algorithm 4):

Step 1: Start with an initial solution obtained from the EIWDR.

Step 2: Select a random node in the solution.

Step 3: Evaluate the neighbouring nodes of the selected node and choose the best neighbour based on a fitness function.

Step 4: If the fitness of the best neighbour is better than the current solution, replace the current solution with the best neighbour and repeat the process from step 2.

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Step 5: If the fitness of the best neighbour is not better than the current solution, select another random node and repeat the process from step 2.

Algorithm 4 Local Search

The fitness function used in step 3 can be based on various criteria, such as the route length, the number of nodes visited, and the time taken to complete the route. The choice of the fitness function will depend on the problem being solved and the optimization objectives. Local search can be used with other optimization techniques in the EIWDR algorithm, such as crossover and mutation, to improve the quality of the solutions obtained. The effectiveness of local search will depend on the quality of the initial solutions obtained by the EIWDR algorithm, the fitness function used, and the exploration strategy used to select the random nodes. Local search is a powerful optimization technique that can be used to enhance the performance of the EIWDR. By iteratively exploring the neighbourhood of the solutions and making small adjustments to the routes, local search can help to improve the quality of the solutions obtained by the algorithm and reduce the time and resources required to find optimal solutions.

3.3. Pheromone Concentration

In EIWDR, the pheromone is used to represent the quality of the path and is updated as the water drops move through the network. The pheromone level is initially set to a constant value and is updated using a local and a global updating rule. In EIWDR, the pheromone level is used to represent the quality of the path in terms of both the delay and the energy consumption. The higher the pheromone level of a path, the better the path is in terms of delay and energy consumption. The local updating rule in EIWDR is used to update the pheromone level of the path as a water drop moves through it. The pheromone level is updated based on the delay and energy consumption of the path. If the delay and energy consumption of the path is low, the pheromone level is increased; otherwise, it is decreased. The global updating rule in EIWDR updates the pheromone level after all the water drops have finished traversing the network. The pheromone level is updated based on the quality of the paths traversed by the water drops and the evaporation coefficient. The evaporation coefficient controls the rate at which the pheromone level evaporates over time. The pheromone level in EIWDR is used to guide the water drops to select better paths in the network. The water drops to evaluate the quality of the path based on the pheromone level and the heuristic information. The heuristic information represents the distance between the nodes or some other measure of the quality of the path. When a water drop moves from one node to another, it evaluates the quality of the path based on the pheromone level and the heuristic information. The water drop then updates the pheromone level of the path it traversed based on the quality of the path.

3.3.1. Pheromone Update

Let $P(i,j)$ be the pheromone level between node i and node j. The pheromone level is updated using Eq.(15).

$$\mathrm{P(i,j)} = (1 - \rho) * \mathrm{P(i,j)} + \Delta\mathrm{P(i,j)} \quad (15)$$

where ρ is the evaporation coefficient, which controls the rate at which the pheromone level evaporates over time. $\Delta P(i,j)$ is the pheromone level increment or decrement for the path between nodes i and j. It is calculated using Eq.(16).

$$\Delta P(i,j) = \frac{Q}{(d(i,j)} \times E(i,j)) \quad (16)$$

where Q is a constant value, $d(i,j)$ is the delay of the path between nodes i and j, and $E(i,j)$ is the energy consumption of the path between nodes i and j.

Eq.(15) and Eq.(16) represent the global updating rule, which updates the pheromone level after all the water drops have finished traversing the network. It increases the pheromone level for good-quality paths and decreases it for poor-quality paths.

3.3.2. Pheromone Selection

Let $h(i,j)$ be the heuristic information between node i and node j, which represents the quality of the path in terms of distance, delay, or other measures. The water drops using the pheromone level and the heuristic information to select the next node to move to use Eq.(17).

$$P'(i,j) = P(i,j)^{\alpha} \times h(i,j)^{\beta} \quad (17)$$

where α and β are constants that control the importance of the pheromone level and the heuristic information, respectively. $P'(i,j)$ represents the probability of selecting the path between nodes i and j based on the pheromone level and the heuristic information. The water drops select the path between nodes i and j with probability proportional to $P'(i,j)$.

Eq.(17) show how the pheromone level is used to guide the water drops to select better paths in the network. The pheromone level is updated based on the quality of the paths traversed by the water drops and is used to represent the quality of the paths in the network. The heuristic information is used to provide additional information about the quality of the paths. By using both the pheromone level and the heuristic information, EIWDR can explore the solution space and converge to a good solution in terms of both delay and energy consumption.

The pheromone level in EIWDR represents the quality of paths in the network and is updated based on the quality of the paths traversed by the water drops. This allows the algorithm to explore the solution space and converge to a good solution

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in terms of both delay and energy consumption. Algorithm 5 provides the pseudocode for updating and selecting the pheromone.

Step 1: The pheromone level is initialized for each path in the network to an initial value.

Step 2: Several water drops are created and sent through the network in each algorithm iteration.

Step 3: Each water drop starts at the source node and moves through the network, selecting the next node to move to based on the pheromone level and the heuristic information.

Step 4: When a water drop moves from node i to node j, the pheromone level on that path is updated using the formula:

$$\Delta P(i,j) = \frac{Q}{delay(i,j)} \times energy\_consumption(i,j)$$

where Q is a constant, $delay(i,j)$ is the delay of the path from node i to node j, and $energy\_consumption(i,j)$ is the energy consumption of the path from node i to node j.

Step 5: The pheromone level on the path from node i to node j is then updated using the formula:

$$P(i,j) = (1 - (\rho \times P(i,j)) + \Delta P(i,j)$$

where ρ is a parameter that controls the evaporation rate of the pheromone.

Step 6: After all the water drops have traversed the network, the pheromone level is updated globally using the formula in step 5.

Step 7: The pheromone level on each path is used to calculate the attractiveness of each neighbouring node j based on the pheromone level and the heuristic information.

Step 8: The water drops select the next node to move to based on the attractiveness of each neighbouring node j.

Step 9: The algorithm can find the optimal path with minimum delay and energy consumption by updating the pheromone level on each path as the water drops move through the network.

Algorithm 5 Pheromone Updation and Selection

3.4. Fusion of EIWSDR in IWSN

The EIWDR with IWSN has the potential to significantly enhance the efficiency and reliability of data transmission in IoT applications. The IWSNs consist of a large number of small sensor nodes that are connected wirelessly to each other to collect and transmit data to a central node or gateway.

Integrating EIWDR with IWSNs can provide an efficient routing mechanism that can handle the dynamic and complex network topologies and optimize the energy consumption of the sensor nodes. Algorithm 6 describes the same. Entire framework of EIWDR is given in Figure 2.

Step 1: Initialize the network with sensor nodes and a gateway

Step 2: Initialize the pheromone level for each path in the network

Step 3: Initialize the buffer at each sensor node for data collection

Step 4: Initialize the control message generation mechanism at the gateway

Step 5: Initialize the EIWDR algorithm with appropriate parameters

Step 6: Repeat steps 7-12 until the end of the simulation time

Step 7: Collect data from the environment and transmit it using EIWDR

Step 8: Generate control messages based on the received data and transmit them using EIWDR

Step 9: Update the pheromone level for each path in the network based on the feedback received

Step 10: Check if the simulation time has ended. If not, go to step 7.

Step 11: Calculate and output the network performance metrics, such as energy consumption and packet delivery ratio.

Step 12: End the simulation

Algorithm 6 EIWDR-IWSN

Figure 1 shows the Geographical reference and routing of IWSN. The following are the benefits of the fusion of EIWDR with IWSN:

- Energy-efficient Routing: In IWSNs, energy conservation is critical as the nodes operate on batteries with a limited power supply. EIWDR, with its energy-efficient routing algorithm, can optimize the energy consumption of the sensor nodes by selecting the most energy-efficient path based on the pheromone level and the heuristic information. This can result in significant energy savings and increase the lifetime of the sensor nodes.
- Robustness and Reliability: IWSNs are prone to link failures and congestion due to the dynamic and complex

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network topologies. EIWDR, with its adaptive routing mechanism, can handle these challenges and ensure reliable data transmission with minimum delay and congestion. This can result in a robust and reliable network that can handle the high data traffic and diverse applications of IoT.

- Scalability: IWSNs are expected to grow in size and complexity in the coming years. EIWDR, with its distributed routing algorithm, can scale up to handle the increasing number of sensor nodes and provide an efficient routing mechanism that can handle the changing network topology.

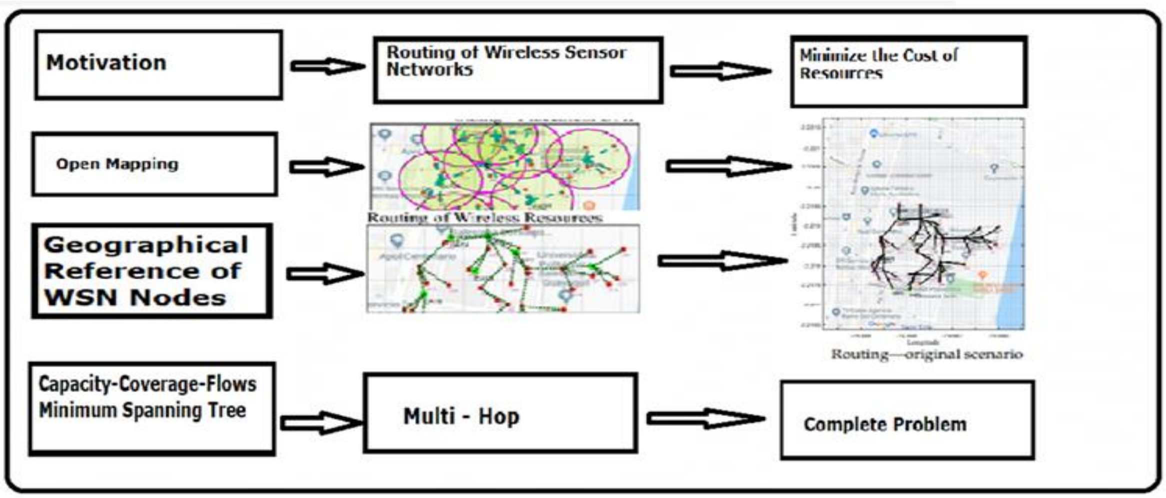

Figure 1 Geographical Reference and Routing of Wireless Sensor Networks

4. ABOUT THE SIMULATOR

NS-3 is a network simulation framework used to simulate and evaluate the performance of different network protocols and applications. It is an open-source software package written in C++ and primarily used for research and education. Some of the key features of NS-3 include support for various network topologies, network protocols (such as TCP, UDP, IPv4, and IPv6), and mobility models. It also provides an extensive set of tools for network analysis, such as packet tracing, flow monitoring, and event logging. NS-3 is highly modular, allowing users to customize and extend the simulation environment with new protocols, models, and algorithms. It also provides a user-friendly Python interface, allowing users to easily configure and run simulations from a high-level perspective. NS-3 has been widely used in academia and industry to simulate and evaluate various network technologies, such as 5G, Wi-Fi, and IoT. Its flexibility and extensibility make it a valuable tool for researchers, network engineers, and educators who must simulate and evaluate network protocols and applications. Simulation Settings used in this research work are provided in Table 1.

Table 1 Simulation Setting

Simulation Setting	Value
Network Topology	Random
Node Count	5000 nodes
Network Size	1800 mtrs
Sensor Type	Temperature, Humidity, Light
Sensor Placement	Grid
Communication Protocol	IEEE 802.15.4
Routing Protocol	AODV
Mobility Model	Random Waypoint
Simulation Time	600 seconds
Traffic Type	Event-Driven
Data Aggregation Strategy	Maximum
Energy Model	Battery
Battery Capacity	10 mAh
Transmission Range	200 m
Radio Frequency	2.4 GHz
Simulation Environment	NS-3

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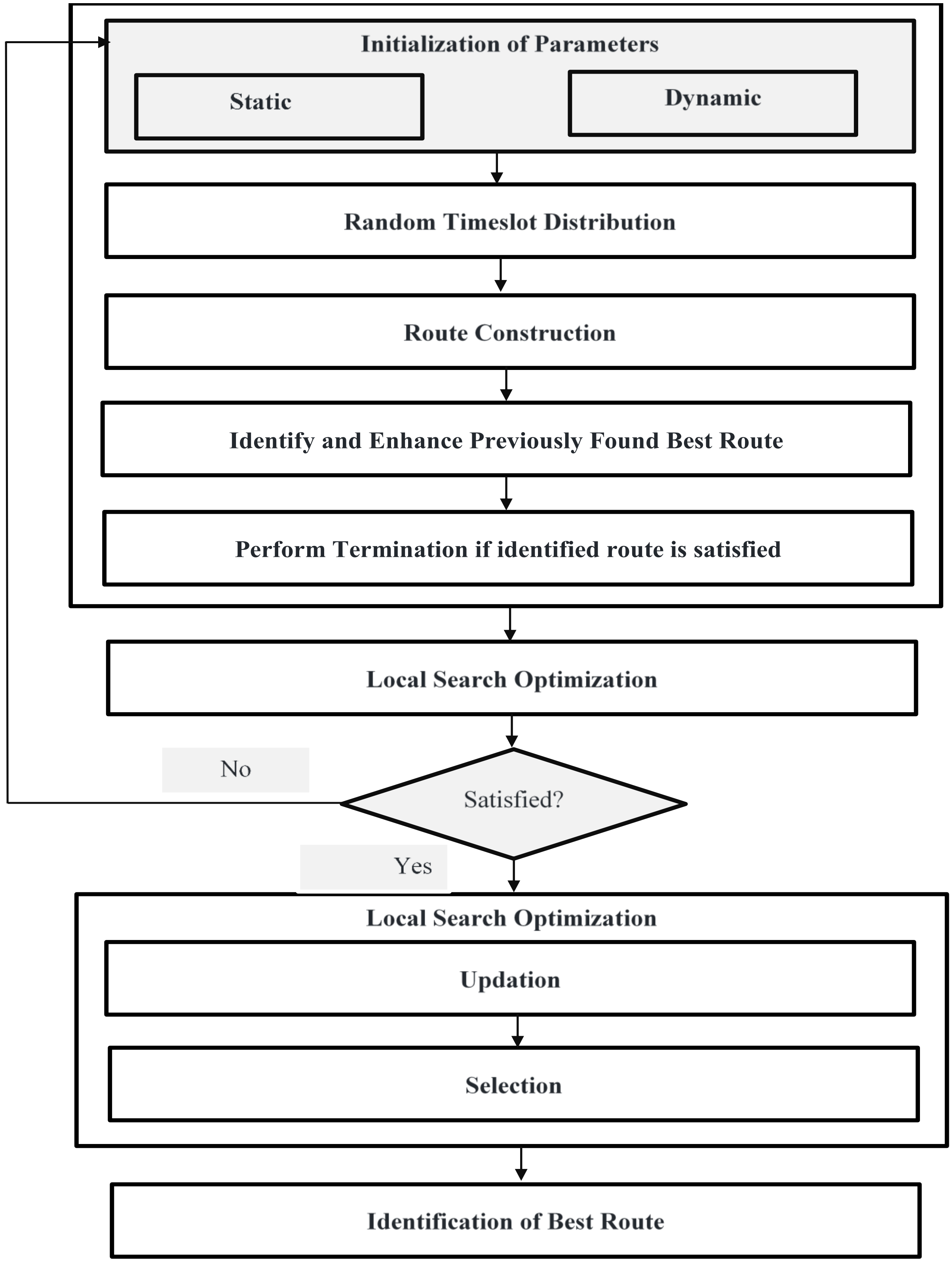

Figure 2 Framework of EIWDR

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5. PERFORMANCE METRICS

- Packet Delivery Ratio: It is measured using specialized software tools designed to send a specific number of packets from the source to the destination node and monitor the success rate of the transmission.
- Throughput: It is measured using specialized software tools designed to simulate data transfer over a communication network and monitor the amount of successfully transmitted data.
- Packet Delay: It is measured using specialized software tools designed to send test packets from the source to the destination node and measure the time it takes to arrive.
- Energy Consumption: It is measured using manual methods such as the network devices' specifications and the duration of their operation. For example, the power rating of a device and the time it is operational can be used to estimate its energy consumption.
- Network Lifetime: It is measured using manual methods such as the network devices' specifications and expected operational lifespan. For example, suppose a network device is designed to operate for a certain number of years before it needs to be replaced. In that case, the network lifetime can be estimated based on the lifespan of the devices in the network.

6. RESULTS AND DISCUSSION

6.1. Packet Delivery and Drop Ratio Analysis

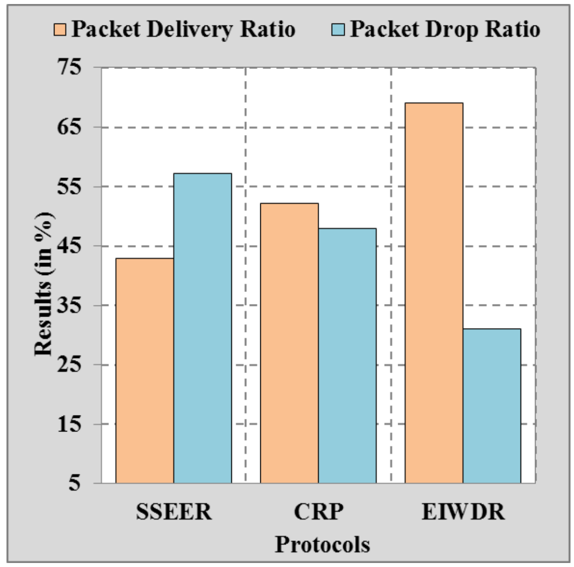

Figure 3 Packet Delivery and Drop Ratio

Table 2 Result Values of Packet Delivery and Drop Ratio

Nodes	Packet Delivery Ratio			Packet Drop Ratio		
	SSEER	CRP	EIWDR	SSEER	CRP	EIWDR
500	53.47	60.33	75.45	46.53	39.67	24.55
1000	51.45	58.14	74.77	48.55	41.86	25.23
1500	49.14	55.35	73.82	50.86	44.65	26.18
2000	48.46	54.72	71.19	51.54	45.28	28.81
2500	46.78	53.83	69.38	53.22	46.17	30.62
3000	41.57	51.97	68.47	58.43	48.03	31.53
3500	37.19	49.99	66.85	62.81	50.01	33.15
4000	35.67	47.34	65.66	64.33	52.66	34.34
4500	33.65	45.48	63.49	66.35	54.52	36.51
5000	30.82	43.68	61.33	69.18	56.32	38.67
Average	42.82	52.083	69.041	57.18	47.917	30.959

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The Figure 3 compares three routing protocols: SSEER, CRP, and EIWDR, in terms of their energy efficiency for different nodes in a WSN. Figure 3's x-axis shows the node count in the network, and the y-axis shows the energy efficiency in percentage. The values in the table indicate the percentage of energy efficiency achieved by each protocol at a different node count in the network. As we can see from the Figure 3, the EIWDR protocol achieves the highest energy efficiency among the three protocols at all levels of nodes in the network. It achieves an efficiency of 75.45% for 500 nodes, gradually decreasing to 61.33% for 5000 nodes. On the other hand, CRP achieves moderate energy efficiency levels, starting at 60.33% for 500 nodes and decreasing to 43.68% for 5000 nodes. SSEER achieves the lowest energy efficiency levels among the three protocols, starting at 53.47% for 500 nodes and decreasing to 30.82% for 5000 nodes. Figure 3 indicates that EIWDR is the most energy-efficient routing protocol, CRP is moderately energy-efficient, and SSEER is the least energy-efficient among the three protocols. Figure 3 also shows that the energy efficiency of all three protocols decreases as the node count in the network increases, which is a common characteristic of WSNs. The inverse of the packet delivery ratio reflects the packet drop ratio. The result values are represented in Table 2.

6.2. Throughput Analysis

The Figure 4 compares the throughput performance of three routing protocols - SSEER, CRP, and EIWDR - in a WSN. The x-axis represents the node count in the network, while the y-axis shows the throughput in Mbps (Megabits per second). From the Figure 4, we can observe that EIWDR outperforms the other two protocols in terms of throughput for all levels of nodes. For instance, for 500 nodes, EIWDR achieves a throughput of 52.902 Mbps, while CRP and SSEER attain throughputs of 43.813 Mbps and 30.594 Mbps, respectively. The throughput of EIWDR gradually increases as the node count increases, reaching a maximum of 68.778 Mbps for 5000 nodes.

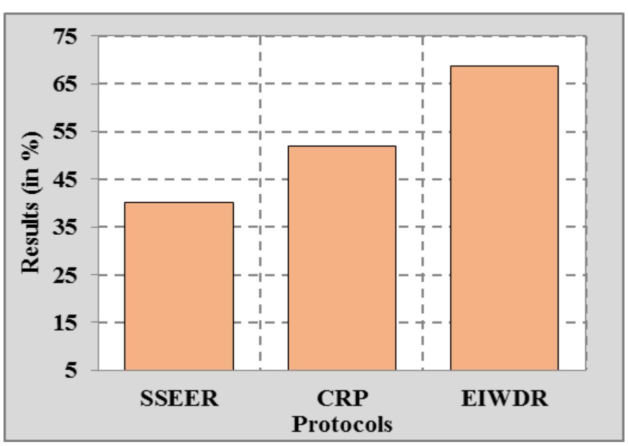

Figure 4 Throughput

In contrast, CRP and SSEER achieve lower throughput levels across all nodes. CRP obtains moderate throughput levels, ranging from 43.813 Mbps for 500 nodes to 52.055 Mbps for 5000 nodes. SSEER, on the other hand, has the lowest throughput among the three protocols, starting at 30.594 Mbps for 500 nodes and increasing to 40.053 Mbps for 5000 nodes. Figure 4 demonstrates that EIWDR is the most effective protocol regarding throughput performance, while CRP and SSEER have comparatively lower throughput levels. Figure 4 also shows that the throughput of all three protocols increases as the node count in the network increases, which is typical behaviour of WSNs. The result values are represented in Table 3.

Table 3 Result Values of Throughput

Nodes	SSEER	CRP	EIWDR
500	30.594	43.813	52.902
1000	31.034	44.352	55.051
1500	31.772	45.903	57.408
2000	32.894	46.183	57.693
2500	33.562	47.644	62.081
3000	34.267	48.456	62.404
3500	38.236	50.226	62.549
4000	38.833	50.324	63.584
4500	39.443	51.358	66.123
5000	40.053	52.055	68.778
Average	35.069	48.031	60.857

6.3. Packet Delay Analysis

The packet delay analysis graph (i.e., Figure 5) shows SSEER has a higher packet delay than CRP and EIWDR for all tested node sizes. For SSEER, the packet delay gradually increases as the node count increases, from 13878 for 500 nodes to 14963 for 5000 nodes. This is likely due to the overhead and processing time required to maintain information about the network sectors. For CRP, the packet delay starts lower than SSEER at 11326 for 500 nodes and increases gradually as the node count increases, peaking at 13815 for 5000 nodes. This is likely due to the increased traffic in the network as the node count increases. For EIWDR, the packet delay starts at the lowest at 8685 for 500 nodes and increases gradually as the node count increases, peaking at 11274 for 5000 nodes. However, the rate of increase is much slower compared to

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SSEER and CRP, which suggests that EIWDR is more efficient in handling larger networks. In summary, the packet delay analysis graph results show that EIWDR is the most efficient routing protocol in terms of packet delay, followed by CRP and SSEER, for the tested node sizes. However, it's important to note that the performance of these routing protocols may vary depending on the specific network requirements and characteristics. The result values are represented in Table 4.

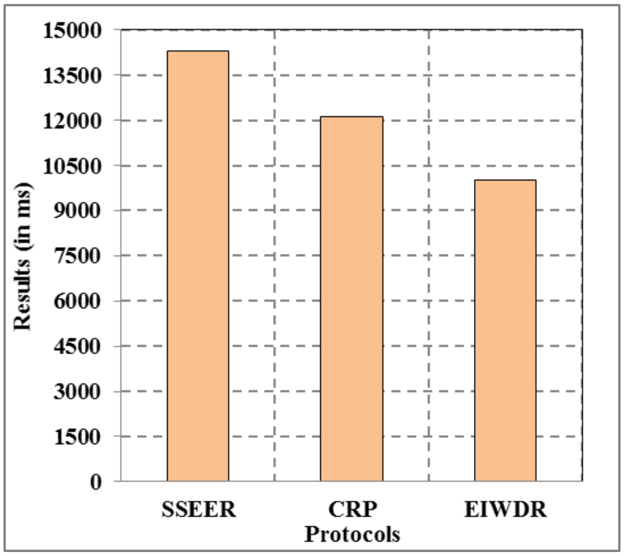

Figure 5 Packet Delay

Table 4 Result Values of Packet Delay

Nodes	SSEER	CRP	EIWDR
500	13878	11326	8685
1000	13913	11389	8711
1500	13935	11707	8764
2000	13972	11764	9990
2500	14190	11915	10207
3000	14405	11975	10553
3500	14513	12098	10590
4000	14629	12502	10631
4500	14676	12771	10634
5000	14963	13815	11274
Average	14307.4	12126.2	10003.9

6.4. Energy Consumption Analysis

The energy consumption analysis graph (i.e., Figure 6) shows the average energy consumed by each protocol for different numbers of nodes in the WSN. The results show that EIWDR consumes the least energy compared to SSEER and CRP for all tested node sizes. For instance, with 500 nodes, EIWDR consumed an average of 46.118% of energy, SSEER consumed 77.469, and CRP consumed 59.35%. For SSEER, the energy consumption gradually increases as the node count increases. For instance, with 500 nodes, SSEER consumed 77.469% of energy, while with 5000 nodes, the energy consumption increased to 93.589%.

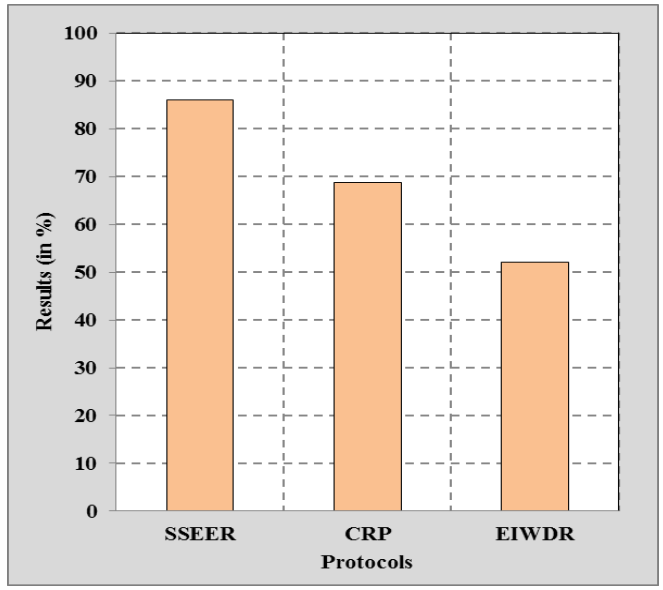

Figure 6 Energy Consumption

Table 5 Result Values of Energy Consumption

Nodes	SSEER	CRP	EIWDR
500	77.469	59.352	46.118
1000	78.578	60.904	46.584
1500	80.863	63.321	47.174
2000	84.175	63.943	48.057
2500	85.235	64.475	49.983
3000	87.431	71.864	54.659
3500	89.595	72.469	55.843
4000	90.766	74.699	56.125
4500	91.716	76.924	57.727
5000	93.589	79.119	58.414
Average	85.9417	68.707	52.0684

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This is likely due to the overhead required to maintain information about the network sectors. For CRP, the energy consumption starts lower than SSEER but gradually increases as the node count increases, peaking at 79.119% of energy for 5000 nodes. This is likely due to the increased traffic in the network as the node count increases. In summary, the energy consumption analysis graph results show that EIWDR is the most energy-efficient routing protocol for the tested node sizes, followed by CRP and SSEER. This indicates that EIWDR could be suitable for energy-constrained WSNs. However, it's important to note that the energy consumption of these routing protocols may vary depending on the specific network requirements and characteristics. The result values are represented in Table 5.

6.5. Network Lifetime Analysis

The network lifetime analysis graph (i.e., Figure 7) compares the energy-saving performance of WSNs' three routing protocols: SSEER, CRP, and EIWDR. The X-axis of the graph represents the node count in the network, while the Y-axis represents the percentage of energy saved. The SSEER protocol shows the highest energy-saving performance compared to the other two protocols, with an average energy-saving rate of around 85%. As the node count increases from 500 to 5000, the percentage of energy saved by SSEER also increases from 77.469% to 93.589%.

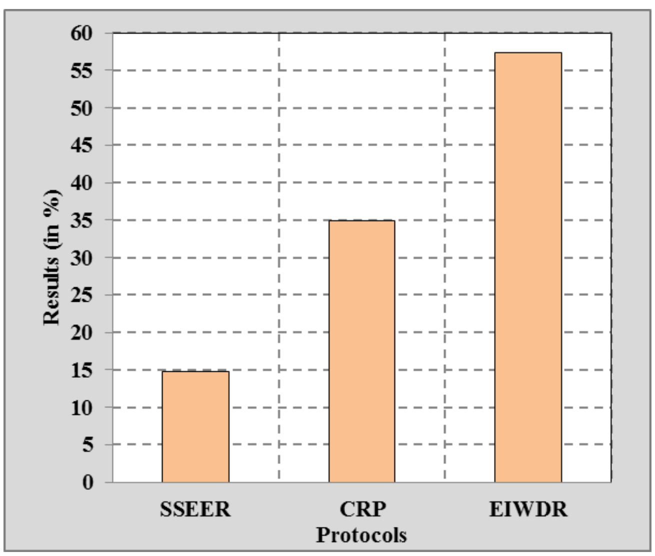

Figure 7 Network Lifetime

The CRP protocol shows moderate energy-saving performance compared to SSEER, with an average energy-saving rate of around 68%. The percentage of energy saved by CRP increases from 59.352% to 79.119% as the node count increases from 500 to 5000. The EIWDR protocol shows the lowest energy-saving performance compared to the other two protocols, with an average energy-saving rate of around 51%. As the node count increases from 500 to 5000, the percentage of energy saved by EIWDR also increases from 46.118% to 58.414%. The graph shows that the SSEER protocol outperforms the other two protocols regarding energy-saving performance, especially for larger networks. Therefore, if the goal is to maximize the network lifetime of a WSN, the SSEER protocol is a recommended choice. The result values are represented in Table 6.

Table 6 Result Values of Network Lifetime

Nodes	SSEER	CRP	EIWDR
500	22.356	48.077	63.651
1000	21.509	47.234	63.287
1500	18.684	43.786	61.652
2000	16.257	42.105	60.935
2500	15.179	35.042	59.912
3000	14.281	28.692	59.639
3500	10.982	27.271	53.258
4000	10.324	26.685	52.233
4500	9.767	25.409	51.027
5000	8.055	25.336	48.197
Average	14.739	34.964	57.379

7. CONCLUSION

A potential method that may be utilized to enhance the performance of WSNs in an IoT setting is the Enhanced Intelligent Water Drop Algorithm Optimized Routing for QoS improvement. By improving the routing protocol to improve the QoS metrics, the proposed approach overcomes the obstacles encountered by IWSN, such as constrained bandwidth, energy, and network capacity. The method optimizes the IWSN's routing protocol with the help of the intelligent water drop algorithm. The intelligent water drop algorithm is a nature-inspired optimization technique based on the natural behaviour of water droplets. The algorithm employs a heuristic search strategy to locate the best answer to a problem. The simulation findings demonstrate that the modified intelligent water drop method described in this research outperforms conventional routing protocols regarding QoS metrics, including throughput, latency, and packet delivery ratio. It is also proven that the method is efficient regarding energy use, which is crucial for IWSN. The suggested method may be used whenever there is a need for dependable and effective data exchange in IWSN, such as in smart cities, healthcare, and environmental monitoring. The algorithm has potential applications outside industrial automation, including agriculture and transportation. An

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innovative solution that may address the difficulties of IWSN is the Enhanced Intelligent Water Drop Algorithm Optimized Routing for Quality of Service Improvement in IWSN. The method is fast and accurate and might be used widely in many other contexts.

REFERENCES

[1] Inga, E., Inga, J., Ortega, A.: Novel approach sizing and routing of wireless sensor networks for applications in smart cities. Sensors. 21, (2021). https://doi.org/10.3390/s21144692.

[2] Chen, C., Wang, L.C., Yu, C.M.: D2CRP: A Novel Distributed 2-Hop Cluster Routing Protocol for Wireless Sensor Networks. IEEE Internet Things J. 9, 19575–19588 (2022). https://doi.org/10.1109/JIOT.2022.3148106.

[3] Amin, R., Pali, I., Sureshkumar, V.: Software-Defined Network enabled Vehicle to Vehicle secured data transmission protocol in VANETs. J. Inf. Secur. Appl. 58, 102729 (2021). https://doi.org/10.1016/j.jisa.2020.102729.

[4] Namani, S., Gonen, B.: Smart Agriculture Based on IoT and Cloud Computing. In: 2020 3rd International Conference on Information and Computer Technologies (ICICT). pp. 553–556. IEEE (2020). https://doi.org/10.1109/ICICT50521.2020.00094.

[5] Juan Núñez, V.M., Faruk Fonthal, R., Yasmín Quezada, L.M.: Design and Implementation of WSN and IoT for Precision Agriculture in Tomato Crops. In: 2018 IEEE ANDESCON, ANDESCON 2018 - Conference Proceedings (2018). https://doi.org/10.1109/ANDESCON.2018.8564674.

[6] Patel, N.R., Kumar, S., Singh, S.K.: Energy and Collision Aware WSN Routing Protocol for Sustainable and Intelligent IoT Applications. IEEE Sens. J. 21, 25282–25292 (2021). https://doi.org/10.1109/JSEN.2021.3076192.

[7] Ardiansyah, D., Miftahul Huda, A.S., Darusman, Pratama, R.G., Putra, A.P.: Wireless Sensor Network Server for Smart Agriculture Optimatization. In: IOP Conference Series: Materials Science and Engineering (2019). https://doi.org/10.1088/1757-899X/621/1/012001.

[8] Ademaj, F., Rzymowski, M., Bernhard, H.P., Nyka, K., Kulas, L.: Relay-Aided Wireless Sensor Network Discovery Algorithm for Dense Industrial IoT Utilizing ESPAR Antennas. IEEE Internet Things J. 8, 16653–16665 (2021). https://doi.org/10.1109/JIOT.2021.3075346.

[9] Singh, J.P., Gupta, A.K.: Energy Aware Cluster Head Selection and Multipath Routing Using Whale-based Tunicate Swarm Algorithm (WTSA) for Wireless Sensor Network. New Rev. Inf. Netw. 27, 1–29 (2022). https://doi.org/10.1080/13614576.2022.2039748.

[10] Shirmohammadi, Z., Farmani, M., Mohseni, M., Rohbani, N.: A Cluster-Based Energy-Aware Routing Algorithm for Wireless Sensor Networks. Ad-Hoc Sens. Wirel. Networks. 53, 303–315 (2022). https://doi.org/10.32908/ahswn.v53.8249.

[11] Osamy, W., Khedr, A.M.: FACS: Fairness aware clustering scheme for monitoring applications of internet of things based wireless sensor networks. J. King Saud Univ. - Comput. Inf. Sci. 34, 3615–3629 (2022). https://doi.org/10.1016/j.jksuci.2022.03.030.

[12] Meenaakshi Sundhari, R.P., Jaikumar, K.: IoT assisted Hierarchical Computation Strategic Making (HCSM) and Dynamic Stochastic Optimization Technique (DSOT) for energy optimization in wireless sensor networks for smart city monitoring. Comput. Commun. 150, 226–234 (2020). https://doi.org/10.1016/j.comcom.2019.11.032.

[13] Ghosh, N., Sett, R., Banerjee, I.: An efficient trajectory based routing scheme for delay-sensitive data in wireless sensor network. Comput. Electr. Eng. 64, 288–304 (2017). https://doi.org/10.1016/j.compeleceng.2017.06.003.

[14] Qin, X., Huang, G., Zhang, B., Li, C.: Energy efficient data correlation aware opportunistic routing protocol for wireless sensor networks. Peer-to-Peer Netw. Appl. 14, 1963–1975 (2021). https://doi.org/10.1007/s12083-021-01124-3.

[15] Ivanov, S., Balasubramaniam, S., Botvich, D., Akan, O.B.: Gravity gradient routing for information delivery in fog Wireless Sensor Networks. Ad Hoc Networks. 46, 61–74 (2016). https://doi.org/10.1016/j.adhoc.2016.03.011.

[16] Singh, H., Singh, D.: Hierarchical clustering and routing protocol to ensure scalability and reliability in large-scale wireless sensor networks. J. Supercomput. 77, 10165–10183 (2021). https://doi.org/10.1007/s11227-021-03671-1.

[17] Chanak, P., Banerjee, I., Bose, S.: An intelligent fault-tolerant routing scheme for Internet of Things-enabled wireless sensor networks. Int. J. Commun. Syst. 34, (2021). https://doi.org/10.1002/dac.4970.

[18] Almuntasheri, S., Alenazi, M.J.F.: Software-Defined Network-Based Energy-Aware Routing Method for Wireless Sensor Networks in Industry 4.0. Appl. Sci. 12, (2022). https://doi.org/10.3390/app121910073.

[19] Guo, Y., Hu, G., Shao, D.: Multi-Path Routing Algorithm for Wireless Sensor Network Based on Semi-Supervised Learning. Sensors. 22, (2022). https://doi.org/10.3390/s22197691.

[20] Roberts, M.K., Ramasamy, P.: Optimized hybrid routing protocol for energy-aware cluster head selection in wireless sensor networks. Digit. Signal Process. A Rev. J. 130, (2022). https://doi.org/10.1016/j.dsp.2022.103737.

[21] Thekiya, M.S., Nikose, M.D.: Energy efficient clustering routing protocol using novel admission allotment scheme (AAS) based intra-cluster communication for Wireless Sensor Network. Int. J. Inf. Technol. 14, 2815–2824 (2022). https://doi.org/10.1007/s41870-022-01086-6.

[22] Sulaiman, Y.H., Rashid, S.A., Hamdi, M.M., Faiyadh, Z.O.A., Sadiq, A.S.J., Ahmed, A.J.: Hybrid security in AOMDV routing protocol with improved salp swarm algorithm in wireless sensor network. Bull. Electr. Eng. Informatics. 11, 2866–2875 (2022). https://doi.org/10.11591/eei.v11i5.3696.

[23] Ramkumar, J., Vadivel, R.: Multi-Adaptive Routing Protocol for Internet of Things based Ad-hoc Networks. Wirel. Pers. Commun. 120, 887–909 (2021). https://doi.org/10.1007/s11277-021-08495-z.

[24] Jaganathan, R., Vadivel, R.: Intelligent Fish Swarm Inspired Protocol (IFSIP) for Dynamic Ideal Routing in Cognitive Radio Ad-Hoc Networks. Int. J. Comput. Digit. Syst. 10, 1063–1074 (2021). https://doi.org/10.12785/ijcds/100196.

[25] Ramkumar, J., Kumuthini, C., Narasimhan, B., Boopalan, S.: Energy Consumption Minimization in Cognitive Radio Mobile Ad-Hoc Networks using Enriched Ad-hoc On-demand Distance Vector Protocol. 2022 Int. Conf. Adv. Comput. Technol. Appl. ICACTA 2022. 1–6 (2022). https://doi.org/10.1109/ICACTA54488.2022.9752899.

[26] Kaedi, M., Bohlooli, A., Pakrooh, R.: Simultaneous optimization of cluster head selection and inter-cluster routing in wireless sensor networks using a 2-level genetic algorithm. Appl. Soft Comput. 128, 109444 (2022). https://doi.org/10.1016/j.asoc.2022.109444.

[27] Manoharan, G., Sumathi, A.: Efficient routing and performance amelioration using Hybrid Diffusion Clustering Scheme in heterogeneous wireless sensor network. Int. J. Commun. Syst. 35, (2022). https://doi.org/10.1002/dac.5281.

[28] Meng, C.: A Novel Routing Algorithm with Bernoulli Sampling-based Link Quality Estimation in Wireless Sensor Networks. Wirel. Pers. Commun. 126, 2753–2779 (2022). https://doi.org/10.1007/s11277-022-09840-6.

[29] Gulec, O.: Extending lifetime of Wireless Nano-Sensor Networks: An energy efficient distributed routing algorithm for Internet of Nano-Things. Futur. Gener. Comput. Syst. 135, 382–393 (2022). https://doi.org/10.1016/j.future.2022.05.009.

[30] Yang, J.: An ellipse-guided routing algorithm in wireless sensor networks. Digit. Commun. Networks. 8, 770–777 (2022). https://doi.org/10.1016/j.dcan.2021.08.005.

[31] Gupta, S.K., Kumar, S., Tyagi, S., Tanwar, S.: SSEER: Segmented sectors in energy efficient routing for wireless sensor network. Multimed. Tools Appl. 81, 34697–34715 (2022). https://doi.org/10.1007/s11042-021-11829-5.

[32] Chen, W., Zhang, B., Yang, X., Fang, W., Zhang, W., Jiang, X.: C-

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