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Statistical Median Regressed Elitist Divergence Squirrel Search Optimization for Energy Aware Data Forwarding in WSN

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A Wireless Sensor Network (WSN) comprises randomly spatially distributed sensor nodes and a base station that communicate with each other through wireless communication channels. In WSNs, forest fires are a major cause of large-scale destruction in forest ecosystems. In a WSN-based forest fire detection system, sensor nodes are strategically deployed in the forest area to monitor events and transmit sensed data to the remote base station. During data transmission, energy efficiency and reliability are crucial factors in the bandwidth-constrained WSN. To enhance energy efficient data forwarding, a novel Statistical Median Regressed Elitist Divergencive Squirrel Search Optimization (SMREDSSO) technique is developed for efficient forest fire detection in WSNs with lower delay and energy consumption. The SMREDSSO technique comprises two processes namely regression and optimization. Firstly, a Wilcoxon signed-statistical repeated median regression analysis is conducted in the WSN to examine node residual energy and bandwidth. Through regression analysis, energy- and bandwidth-efficient sensor nodes are selected in the WSN. Following this, data forwarding is executed from the source node to the destination using the Elitist Divergencive Squirrel Search Optimization method. Energy and bandwidth-efficient sensor nodes are considered as inputs for the optimization process. Subsequently, the distance and better link connectivity between sensor nodes are calculated in fitness. The node with lesser distance and better connectivity is selected for efficient data forwarding in forest fire detection applications. Experimental evaluation is conducted on factors such as energy consumption, packet delivery ratio, packet loss, and delay concerning different numbers of sensor nodes and data packets.

Keywords: Wireless Sensor Network (WSN), Data Forwarding, forest fire detection, Wilcoxon signed-statistical repeated median regression, Elitist Divergencive Squirrel Search Optimization.

1. Introduction

WSNs represent a transformative technology in the wireless communication. The fundamental components of a typical WSN include small-sized, low-cost sensor nodes equipped with sensing, processing, and communication capabilities. These nodes are strategically deployed in an area of interest, forming a self-organizing network to collaboratively monitor physical or environmental conditions and transmit data wirelessly to a sink or other base station within the network. There are numerous applications of WSNs including environmental monitoring, healthcare, industrial automation, agriculture, smart cities, and disaster management. In environmental monitoring, WSNs is deployed for forest fire detection to collect data on temperature, humidity, wind levels, and rain, providing valuable insights for research and decision-making.

Energy plays a vital role in WSNs due to the intrinsic constraints of sensor nodes, typically powered by limited energy sources such as batteries. The challenge lies in designing algorithms that optimize energy consumption, thereby extending the network's lifespan. Energy-aware data forwarding specifically addresses the efficient transmission of data packets from source nodes to base stations, considering the resource constraints of individual sensors. To achieve energy-aware data forwarding, various techniques and optimization algorithms have been employed.

The Energy-efficient and Reliable ACO-based Routing Protocol (E-RARP) was designed in [1] for WSNs, aims to achieve optimal communication of forest fire detection application. Although the model enhances energy-efficient data delivery, it does not effectively minimize performance delay in data communication. Energy Efficient Routing based on Incremental Grey Wolf Optimization (EERI-GWO) was introduced in [2] to determine the path between nodes. However, the designed technique did not specifically address the multi-objective problem, and it did not incorporate heterogeneous sensor nodes.

A new localization method was introduced in [3] using support vector machines with the aim of achieving energy-efficient data forwarding for forest fire detection. However, the model failed to be applied for the early detection of forest fires. To enhance the early prediction of forest fires, machine learning techniques were developed as discussed in [4]. However, the designed techniques proved challenging for the development of automatic fire detection tools.

The Butterfly Optimization Algorithm (BOA) was introduced in [5] with the aim of selecting an optimal cluster head to improve communication and extend the network lifetime. However, a novel optimization algorithm has not been implemented to enhance the performance of the WSN. An Energy-Efficient Data Transmission method designed in [6] based on establishing reliable links between nodes to determine the optimal route path. However, the algorithm failed to enhance the energy efficiency of data transmission as the number of nodes increased.

The Energy Soaring-based Routing method was developed in [7] for monitoring the environment to optimize network lifetime and throughput. However, the method failed to incorporate the concept of energy harvesting from the environment. A Learning Automata-based routing approach was designed in [8] to enhance energy efficiency and ensure reliable data delivery by selecting the next node based on the quality of the link. However, it did not take into account node mobility and energy harvesting within the network.

An efficient and stable node routing method was developed in [9] to ensure the stability of transmitted data, minimize energy consumption, and select more stable nodes for packet forwarding. However, it failed to guarantee the model's ability to consistently transfer data throughout the network. The Energy-Efficient Weighted Optimization technique, as developed in [10], focuses on selecting neighbor nodes for detecting forest fires. However, the performance of delay was not effectively minimized in the forest fire detection.

1.1 Proposal contribution

The main contribution of the SMREDSSO technique is listed as given below,

- A novel SMREDSSO technique is introduced to improve data forwarding in WSN includes a regression and optimization.
- The SMREDSSO technique employs a Wilcoxon signed-rank test, a statistical method based on repeated median regression analysis, to select energy and bandwidth-efficient sensor nodes. The aim is to minimize both energy consumption and loss rate in the WSN.
- The Elitist Divergencive Squirrel Search Optimization method is applied to select the next hop based on distance and improved link connectivity. The elitist strategy is utilized to enhance the performance of the optimization process. The Jensen-Shannon divergence is employed to determine the best optimal sensor node. Consequently, the optimization technique improves data delivery and minimizes delay.
- An extensive simulation is conducted to assess the performance of our SMREDSSO technique, as well as other related works, using various performance metrics.

1.2 paper Organization

The remaining paper is organized into different sections as follows. Section 2 discusses related works. Section 3 briefly describes the proposed SMREDSSO technique. Section 4 provides information on the simulation settings, including the dataset description. In Section 5, the simulation outcomes and comparative analysis are presented using various performance metrics. Finally, Section 6 concludes the paper.

2. RELATED WORKS

A machine learning regression model was developed in [11] to enhance the accuracy of detecting forest fires at the initial stage. However, addressing energy-aware forest fire detection was challenging issue. The Energy Efficient Routing Protocol (EERP) was developed [12] with the aim of minimizing energy utilization during the transmission of data for forest fire detection.

A network of wireless sensors and information fusion methods was developed for forest fire detection in [13]. But, this did not incorporate considerations of the energy consumption of the WSN. An ant colony optimization-based algorithm was developed in [14] to construct the shortest path between selected nodes, aiming to increase network lifetime and minimize delay.

The Link Delay Aware Routing (SBLDAR) technique was designed in [15] with aims to increase network lifetime and improve communication performance. A Self-Improved Butterfly Optimization Algorithm was developed in [16] for the transmission of multimedia information with minimal delay. However, it did not achieve a higher delivery ratio.

A new hierarchical approach was introduced in [17] for forest fire detection to enhance the transmission of visual data with energy efficiency. However, the approach did not achieve high-accuracy detection. The Location-Aided Routing (LAR) protocol was designed in [18] for forest fire detection to enhance the packet delivery ratio and minimize transmission delay.

The Oppositional-based Whale Optimization Algorithm was introduced in [19] for multi-constrained Quality of Service (QoS) routing, aiming to enhance the delivery ratio and minimize delay. The forest fire detection system was developed in [20] for early detection using the X-bee module protocol. However, the computational cost for forest fire detection was not improved.

3. PROPOSAL METHODOLOGY

In this section, the proposed methodology is described to address the challenge of energy efficiency in a forest area monitored by a distributed bandwidth-constrained WSN. To improve energy efficiency, data forwarding is an significant process that is being considered in the context of WSNs. A novel technique, SMREDSSO, is developed to optimize the energy requirements of smart sensors, with a specific focus on data transmission for forest fire detection. The SMREDSSO technique comprises two main processes namely regression and optimization, aimed at enhancing data forwarding in WSNs. The architecture diagram of the proposed SMREDSSO technique is presented in Figure 1.

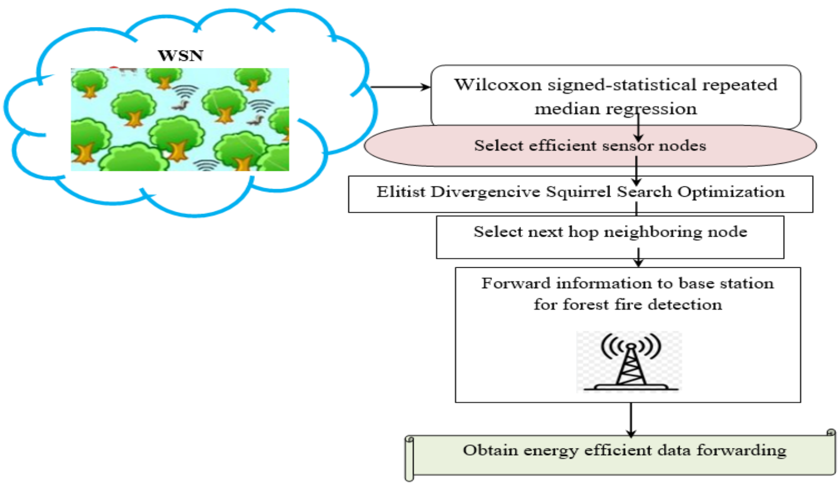

Figure 1 architecture diagram of the proposed SMREDSSO technique

Figure 1 depicts an architecture diagram of the proposed SMREDSSO technique to obtain energy aware data forwarding from sensor nodes to remote base station for forest fire detection applications scenario.

3.1 Network model

In this section, a network model of WSN with a forest fire detection scenario is designed. The WSN is organized in an undirected graph '$G = (V, E)$', where 'V' indicates a sensor nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \ldots . Sn_n$ deployed in a forest area, and 'E' indicates the edges i.e. connection between the sensor nodes. The sensor node (Sn) in forest region collects the fire related information's i.e. data packet$Dp_1, Dp_2, Dp_3, \ldots Dp_n$. The proposed technique identifies energy and bandwidth-efficient sensor nodes for transmitting the collected fire information to a remote base station for further processing. It then selects the optimal next-hop node to enhance data delivery and minimize delay. Based on the aforementioned network model, the SMREDSSO technique is designed.

3.2 Wilcoxon signed-statistical repeated median regression

First process of the proposed SMREDSSO technique is a selection of the energy and bandwidth efficient sensor nodes for forest fire related data transmission in WSN. This process also prolong the network lifetime. This is achieved through the Wilcoxon signed-statistical repeated median regression. It is a machine learning technique used for analyzing the node energy and bandwidth. The main advantage of regression is computationally intensive, especially as the number of iterations increases. It also provides more reliable outcomes. The main purpose of Wilcoxon signed-statistical repeated median regression is to iteratively compute the median of the residuals and update the regression coefficients.

Initially, sensor nodes are deployed in a WSN with similar energy levels. Due to the sensing and monitoring behavior of the sensor nodes, the initial energy levels degrade over time. Therefore, the residual energy and current energy levels of the sensor nodes are measured, as given below:

$$E_{RES} = E_{INI} - E_{CONS} \tag{1}$$

Where, E_{RES} indicates the residual energy measured based on initial energy 'E_{INI}' and the actual energy consumed 'E_{CONS}'. The energy consumption in all sensor nodes is measured

$$E_{CONS} = E_S + E_{PR} \tag{2}$$

Where, E_{CONS} denotes an energy consumption measured based on the energy consumed in sensing 'E_S', energy consumed in processing 'E_{PR}' respectively

The bandwidth is the fundamental resource for transmitting data in a network. The maximum bandwidth is used for gathering and forwarding from the sensor nodes to the base station. The bandwidth represents the rate at which the data transfer capacity of the sensor node in WSN. It is typically measured in bits per second (bps). The formula for the bandwidth is expressed as:

$$BD = \frac{DTr}{T} \tag{3}$$

Where, BD denotes a bandwidth rate in bits per second (bps), DTr indicates a amount of data transmitted in bits, T denotes at the time taken to transmit the data in seconds.

For a paired sample analysis, each node consists of two samples such as residual energy 'E_{RES}' and bandwidth 'BD'.

$$A = \begin{bmatrix} (E_{RES}, BD)_1 \\ (E_{RES}, BD)_2 \\ (E_{RES}, BD)_3 \\ \vdots \\ (E_{RES}, BD)_n \end{bmatrix} \quad (4)$$

Where, A denotes a estimated matrix of sample pair. After that, the pair of samples is sorted in the ascending order. Compute the median of the from the sorted list. The median is a robust measure of central tendency.

$$M = \begin{cases} \left(\frac{n+1}{2}\right) & ; \quad \text{if sample n is odd} \\ \frac{\left(\frac{n}{2}\right)+\left(\frac{n}{2}+1\right)}{2} & ; \quad \text{if sample n is even} \end{cases} \quad (5)$$

Where, M indicates a median of the sample pair, n indicates a number of sample pairs. Based on the above equation (5), median of sample pairs is computed. After that, Wilcoxon signed-rank test is a non-parametric statistical test used to find the efficient sensor nodes based on median of the sample pair.

$$Z = \begin{cases} (E_{RES}, BD)_i > M\,;\ +1 \\ (E_{RES}, BD)_i < M;\ -1 \end{cases} \quad (6)$$

Where, Z denotes a output of the statistical test outcome, if estimated sample pairs is greater than the median'M', then the test returns the positive value '+1'. If estimated sample pairs is lesser than the median'M', then the test returns the negative value '-1'. The positive results are used for finding the energy and bandwidth efficient sensor nodes. The algorithm of the Wilcoxon signed-statistical median regression is given below,

Algorithm 1: Wilcoxon signed-statistical repeated median regression
Input: Number of sensor nodes $Sn_i \in Sn_1, Sn_2, Sn_3, \dots . Sn_n$
Output: Select energy and bandwidth efficient sensor nodes
Begin 1: For each sensor node 'Sn_i' 2. Measure the residual energy using (2) 3. Measure the bandwidth using (3) 4. Construct the matrix using (4) 5. Compute median using (5) 6. if ($(E_{RES}, BD)_i > M$) then

```
7.          Statistical test Z = +1
8.            Select energy and bandwidth efficient sensor nodes
9.        else
10.         Statistical test Z = −1
11.     End if
12. End for
End
```

Algorithm 1 outlines the processing steps of Wilcoxon signed-rank statistical repeated median regression for the selection of energy- and bandwidth-efficient sensor nodes. For each sensor node, the energy and bandwidth are estimated. Subsequently, a matrix is constructed with the estimated energy and bandwidth values. Following this, the median of these values is computed. Sensor nodes with estimated energy and bandwidth greater than the median are then selected as efficient sensor nodes, while the other nodes are removed. The selected energy-efficient sensor nodes are utilized for efficient data forwarding in the WSN.

3.3 Elitist Divergencive Squirrel Search Optimization based data forwarding

The second process of the proposed SMREDSSO technique is data forwarding in WSN by selecting the next hop sensor node using Elitist Divergencive squirrel search optimization. Selecting the next-hop neighboring nodes is a fundamental step in WSN. This process determines the path that the sender transmits the data about the forest fire to base station.

Squirrel Search Optimization is a meta-heuristic nature inspired technique and processed by the dynamic foraging behavior of squirrel through the gliding from one position to another. In periods of warm weather, squirrels exhibit dynamic behavior by gliding between trees in the forest to explore and discover food resources. In this algorithm, squirrel is related to the number of energy and bandwidth efficient sensor nodes and food resources represented as a fitness function. Conversely, during cold weather, the squirrels adopt a less active state, and maintenance of their energy requirements. Once the weather turns warm again, the flying squirrels resume their active exploration and foraging activities. This cyclic process repeats throughout the entire lifespan of the squirrels.

Generate an initial population of squirrels (i.e. number of energy and bandwidth efficient sensor nodes) in search space,

$$\mathrm{Sn}_k = \mathrm{Sn}_1, \mathrm{Sn}_2, \mathrm{Sn}_3, \ldots . \mathrm{Sn}_k \quad (7)$$

Where, Sn_k denotes a 'k' number of energy and bandwidth efficient sensor nodes. For each squirrel, the fitness is estimated based on the distance, link connectivity,

The Euclidean distance between the sensor nodes is measured as follows,

$$d = \sqrt{\sum_{j=1}^{m}\left(\mathrm{Sn}_k - \mathrm{Sn}_j\right)^2} \qquad (8)$$

Where, d denotes a distance between the sensor nodes Sn_k and Sn_j.

The link connectivity between sensor nodes in a WSN is typically determined by the link quality and the distance between nodes. The formula for link connectivity is expressed as:

$$LC = \frac{Q}{d} \quad (9)$$

Where, LC denotes link connectivity between sensor nodes, Q indicates a ink quality, which determined using Received Signal Strength Indicator (RSSI), d denotes a distance.

The RSSI of the sensor node is measured by means of two ray ground model,

$$RSSI = \frac{g_t * g_r * \beta_t^2 * \beta_r^2}{d^4} * p_t \quad (10)$$

Where, RSSI indicates the received signal strength of the sensor node, g_t and g_r represents a transmitter and receiver antenna gain, β_t^2 indicates a height of transmitter antenna, β_r^2 denotes a height of receiver antenna, d indicates the distance between transmitter and receiver antenna, p_t symbolizes a transmitted signal power.

The fitness is estimated as given below,

$$F = (LC > T_{LC}) \&\& (d > T_d) \quad (11)$$

Where,F represents a fitness, LC denotes link connectivity between sensor nodes, d distance between the sensor nodes, T_{LC}, T_d indicates a threshold of the link connectivity and distance. After that, the Elitist strategy is applied to determine the current best solution based on the fitness estimation.

$$ES = \begin{cases} F(Sn_k) > F(Sn_j)\ ; & \text{select best } Sn_k \\ \text{Otherwise}\ ; & \text{select best } Sn_j \end{cases} \quad (12)$$

Where, ES denotes a Elitist selection outcomes, $F(Sn_j)$ denotes a fitness of the neighboring sensor node 'Sn_j',$F(Sn_k)$ denotes a fitness of initial sensor node 'Sn_k'. As a result, the fitness of Sn_k is higher than the fitness of neighboring point $F(Sn_j)$, then the node Sn_k is selected as current best. Otherwise, the 'Sn_j' is selected as a current best.

3.3.1 Generate New Locations through Gliding

In this algorithm, the process of generating new locations through gliding follows the foraging behavior of squirrels. Gliding allows the algorithm to explore the solution space in search of optimal solutions.

$$x_i^{\,n} = x_i + W_k\, H_C * \frac{1}{2}|x_i - x_{best}| \quad (13)$$

Where, $x_i^{\,n}$ denotes a new location of the squirrels, x_i indicates old location of the squirrel, W_k denotes a random gliding distance, H_C indicates a gliding constant, $\frac{1}{2}|x_i - x_{best}|$ indicates a Jensen divergence between the current position of squirrel 'x_i' and 'x_{best}' indicates a best position of the squirrel.

3.3.2. Check Seasonal Monitoring Condition:

The foraging behavior of flying squirrels is considerably affected by seasonal deviation.

Therefore, a seasonal monitoring condition is established to prevent the algorithm from being trapped in local optimal solutions.

$$Sc = \sqrt{(x_i^t - x_{best})^2} \quad (14)$$

Where, Sc denotes a seasonal constant, x_i^t denotes a current solution, x_{best} indicates a current solution.

$$Sc_{mn} = \frac{10\ e^{-6}}{365^{\left({It}/{It_{mx}}\right)*2.5}} \quad (15)$$

Where,Sc_{mn} denotes a minimum seasonal constant, It denotes an iteration, It_{mx} indicates a maximum iteration. The seasonal monitoring condition is verified using the minimum seasonal constant. When $Sc < Sc_{mn}$, indicating the end of winter, flying squirrels lose their ability to navigate the forest and randomly relocate their search positions for a food source. This process continues until the maximum number of iterations is reached. Otherwise, the behaviors of generating new locations and checking the seasonal monitoring condition are repeated.

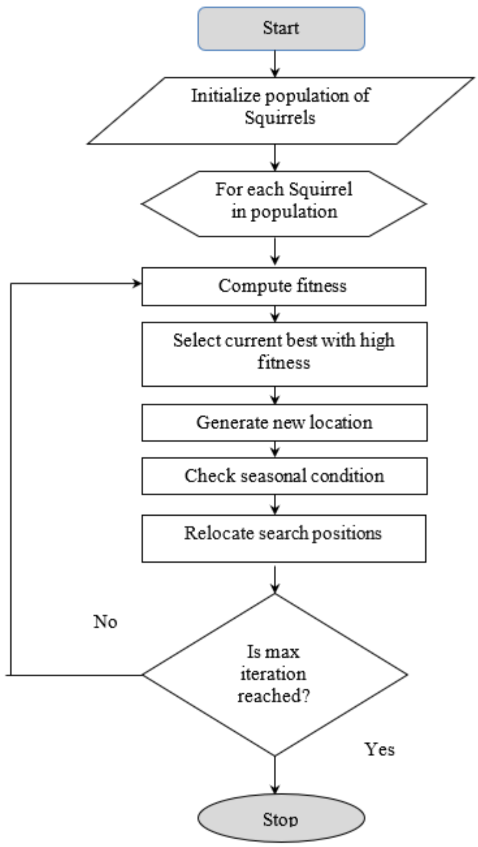

Figure 2 flow chart of Elitist Divergencive Squirrel Search Optimization

Figure 2 illustrates the flow diagram of the Elitist Divergencive squirrel search optimization for selecting the next hop node with minimum distance and better connectivity. As a result, then the optimally selected sensor nodes are selected as a next hop node to forward the information to base station for forest fire detection. In this way, energy efficient data forwarding is performed in WSN for forest fire application. The algorithmic process of Elitist Divergencive squirrel search optimization is given below.

// Algorithm 2: Elitist Divergencive squirrel search optimization

Input: Number of efficient energy and bandwidth sensor nodes $\mathrm{Sn_k} \in \mathrm{Sn_1}, \mathrm{Sn_2}, \mathrm{Sn_3}, \ldots. \mathrm{Sn_k}$, data packets $\mathrm{Dp_1}, \mathrm{Dp_2}, \mathrm{Dp_3}, \ldots \mathrm{Dp_n}$

Output: improve data forwarding

Begin

1: Initialize the population of the sensor nodes $\mathrm{Sn_k} \in \mathrm{Sn_1}, \mathrm{Sn_2}, \mathrm{Sn_3}, \ldots. \mathrm{Sn_k}$

2: for each node in populations

3: Estimate distance and link connectivity using (8), (9) (10)

4: Compute the fitness 'F'

5: While ($\mathrm{It} < \mathrm{It_{mx}}$)

6: Select the current best using (12)

7: Generate new location using (13)

8: Check Seasonal Monitoring Condition using (14)

9: if ($\mathrm{Sc} < \mathrm{Sc_{mn}}$) then

10: Relocate the search space

11: It = It +1

12: go to step 5

13: else

14: Obtain the optimal sensor node

15: end while

16: Select next hop node and forward data packets

End

Algorithm 2, as described above, outlines the process of data forwarding in WSN for a forest fire detection application. The first phase involves generating the initial population of sensor nodes (i.e., squirrels) in the search space. For each sensor node within the population, the proposed optimization technique assesses fitness based on the distance and link connectivity between the sensor nodes. Following fitness evaluation, the current best is selected using an elitist selection strategy. Subsequently, a new position is generated. After that, the seasonal condition is determined and verified with the minimum value. If the seasonal condition is lower than its minimum value, the squirrel relocates in the search space, and the fitness is re-evaluated. This entire process iterates until the algorithm reaches its maximum iterations. This iterative approach enables the Squirrel Search Algorithm to identify optimal sensor nodes. Finally, the sender node selects the optimal next-hop neighboring node, aiming to achieve improved data forwarding with a higher delivery ratio. This overall process enhances the delivery ratio and minimizes the packet loss rate and delay.

4. SIMULATION SETUP

The simulations of the proposed SMREDSSO technique and existing E-RARP [1] , $EER_{I\text{-}GWO}$ [2], are implemented using the NS3 network simulator with forest fire dataset collected from UCI machine learning repository https://archive.ics.uci.edu/dataset/162/forest+fires. Totally, 500 sensor nodes are deployed in a forest area to conduct the simulation. The DSR routing protocol is used to perform energy-efficient data forwarding in WSN. The Random Waypoint model is used as a mobility model. The sensor nodes are used to sense the information of forest weather index, Fine Fuel Moisture Code (FFMC) represents fuel moisture content, Duff Moisture Code(DMC), Drought Code (DC), Initial Spread Index (ISI), temperature , relative humidity , wind speed and rain. Based on the information, the burned area is detected in the forest.

Table 1 Simulation Parameters

Simulation Parameters	Values
Network Simulator	NS3
Simulation area	1100 m * 1100 m
Number of sensor nodes	50,100,150,200,250,300,350,400,450,500
Number of data packets	50,100,150,200,250,300,350,400,450,500
Mobility models communication	Random Waypoint model
Mobility time	0 – 30m/s
Routing Protocol	DSR

4.1 Performance metrics estimation

In this section, evaluate various evolution metrics, including energy consumption, packet delivery ratio, packet loss rate, and delay, to assess the performance of the three different algorithms.

Energy consumption: It is quantified as the amount of energy utilized by sensor nodes during operations such as sensing and data forwarding. This measurement is expressed in joules (J).

$$EN\_C = \sum_{i=1}^{n} Sn_i * EC\ (SSn) \quad (16)$$

Where, EN_C indicates the energy consumption, 'n' indicates the number of sensor nodes 'Sn', $EC\ (SSn)$ indicates a energy consumption for a single sensor node.

Data packet delivery ratio: It is calculated as the ratio of the number of data packets delivered to the base station to the data forwarded by the sensor node. The estimation is provided below,

$$\mathrm{DPDR} = \left(\frac{\mathrm{Dp_{rec}}}{\mathrm{Dp_{sent}}}\right) * 100 \qquad (17)$$

Where DPDR indicates the data packet delivery ratio, $\mathrm{Dp_{rec}}$ denotes data received at the base station, $\mathrm{Dp_{sent}}$ represents the data sent from the sensor node. The delivery ratio is measured in percentage (%).

Data packet loss rate: It is measured as the ratio of the number of data lost at the base station d. Therefore, the loss rate is formulated as given below,

$$\mathrm{DPLR} = \left(\frac{\mathrm{Dp_{lost}}}{\mathrm{Dp_{sent}}}\right) * 100 \qquad (18)$$

Where DPLR represents the data loss rate, $\mathrm{Dp_{lost}}$ indicates a number of data packet lost, $\mathrm{Dp_{sent}}$ represents the data sent from the sensor node. The data loss rate is measured in percentage (%).

Delay: It is referred to as the difference between the actual arrival time of a data packet at the base station and the observed arrival time of data packets. Therefore, the delay is mathematically calculated as follows,

$$\mathrm{Delay} = \left(\mathrm{Time_{AA}(Dp)} - \mathrm{Time_{OA}(Dp)}\right) \qquad (19)$$

Where, , $\mathrm{Time_{AA}(Dp)}$denotes a actual data packet arrival time, $\mathrm{Time_{OA}(Dp)}$ represents the observed arrival time of data packets. The delay is measured in terms of milliseconds (ms).

5. PERFORMANCE RESULTS AND DISCUSSIONS

Performance analysis of the SMREDSSO technique and existing E-RARP [1] , EERI-GWO [2] are discussed in this section with the various metrics such as energy consumption, packet delivery ratio, packet loss rate, and delay. The performances are discussed with the help of a table and graphical representation

Table 2 Comparative analysis of energy consumption

Number of sensor nodes	Energy consumption (joule)		
	SMREDSSO	E-RARP	EERI-GWO
50	22.25	24	26
100	25.5	27	28.2
150	31.5	33	35.25
200	34	36	38.4
250	37.5	40.5	43.75
300	39	42.6	45.6
350	41.3	44.45	46.2
400	42.8	46.8	48.8
450	45.9	48.6	51.75
500	47.5	50.5	52.5

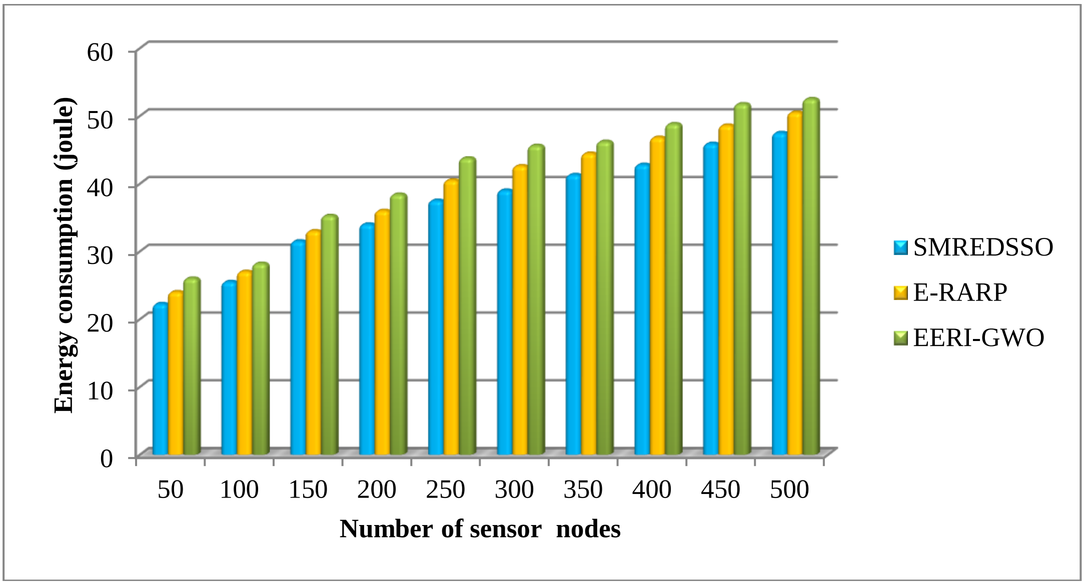

Figure 3 performance results of energy consumption

Figure 3 depicts the performance results of energy consumption versus the number of sensor nodes. As illustrated in Figure 3, the x-axis represents the number of sensor nodes, while the y-axis represents energy consumption in joules. The number of sensor nodes ranges from 50, 100, 150, 200... 500 for ten iterations, using three different methods: SMREDSSO technique, existing E-RARP [1], and EERI-GWO [2]. The observed results show that energy consumption increases for all methods as the number of sensor nodes increases. However, comparatively, the SMREDSSO technique outperforms the other schemes. For instance, considering 50 sensor nodes in the first iteration, the energy consumption using the SMREDSSO technique was 22.25 joules, while the energy consumption using [1] and [2] was observed to be 24 joules and 26 joules, respectively. Similar observations were made for ten different results for each technique. Comparing the performance outcomes of energy consumption for the SMREDSSO technique with existing methods, the analysis reveals that the energy consumption of the proposed SMREDSSO technique is considerably reduced by 7% compared to [1] and 12% compared to [2]. This is because of the application of finding energy-efficient sensor nodes for data forwarding through the Wilcoxon signed-statistical repeated median regression analysis. This improvement is achieved through the application of finding the resource-efficient sensor nodes for data forwarding from source to base station. As a result, the network lifetime gets improved.

Table 3 Comparative analysis of data packet delivery ratio

Number of data packets	Data packet delivery ratio (%)		
	SMREDSSO	E-RARP	EERI-GWO
50	92	88	86
100	94	90	88
150	95.33	88.66	86.66

200	94.5	89.5	87.5
250	92.8	88.8	86.4
300	93.33	89.33	87.33
350	94	90.85	88.57
400	94.5	91.75	89.25
450	95.11	91.11	87.11
500	94.4	89	86.4

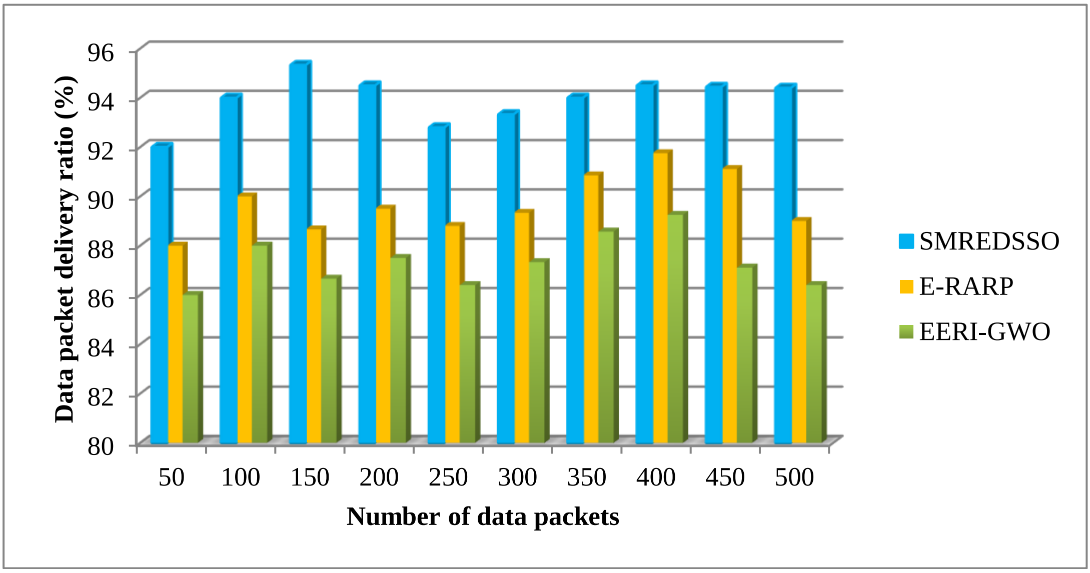

Figure 4 performance results of data packet delivery ratio

Figure 4 depicts the performance outcomes of the packet delivery ratio using three different techniques. The packet delivery ratios are shown on the horizontal axis against the number of data packets on the vertical axis. The number of data packets considered for simulation varies from 50, 100 ... to 500. Among the three methods, the SMREDSSO technique outperforms others in terms of achieving a higher data delivery rate for forest fire detection. Considering the forwarding of 50 data packets in the first iteration, the number of successfully delivered packets at the remote station was 46, resulting in a delivery ratio of 92% for the SMREDSSO technique. Similarly, the packet delivery ratios for [1] and [2] were observed to be 88% and 86%, respectively. Subsequently, the remaining results were obtained and compared. The average of ten comparison results was taken into consideration for the final results. The comparison results conclude that the overall packet delivery ratio of the SMREDSSO technique is significantly improved by 5% and 8% compared to existing methods. The Elitist Divergencive Squirrel Search Optimization method is employed in the SMREDSSO technique to find the next-hop neighboring node with the minimum distance and better link connectivity. This helps enhance data forwarding between the sensor nodes, resulting in improved data delivery for detecting forest fires.

Table 4 Comparative analysis of data packet loss rate

Number of data packets	Data packet loss rate (%)		
	SMREDSSO	E-RARP	EERI-GWO
50	8	12	14
100	6	10	12
150	4.66	11.33	13.33
200	5.5	10.5	12.5
250	7.2	11.2	13.6
300	6.66	10.66	12.66
350	6	9.14	11.42
400	5.5	8.25	10.75
450	5.55	8.88	12.88
500	5.6	11	13.6

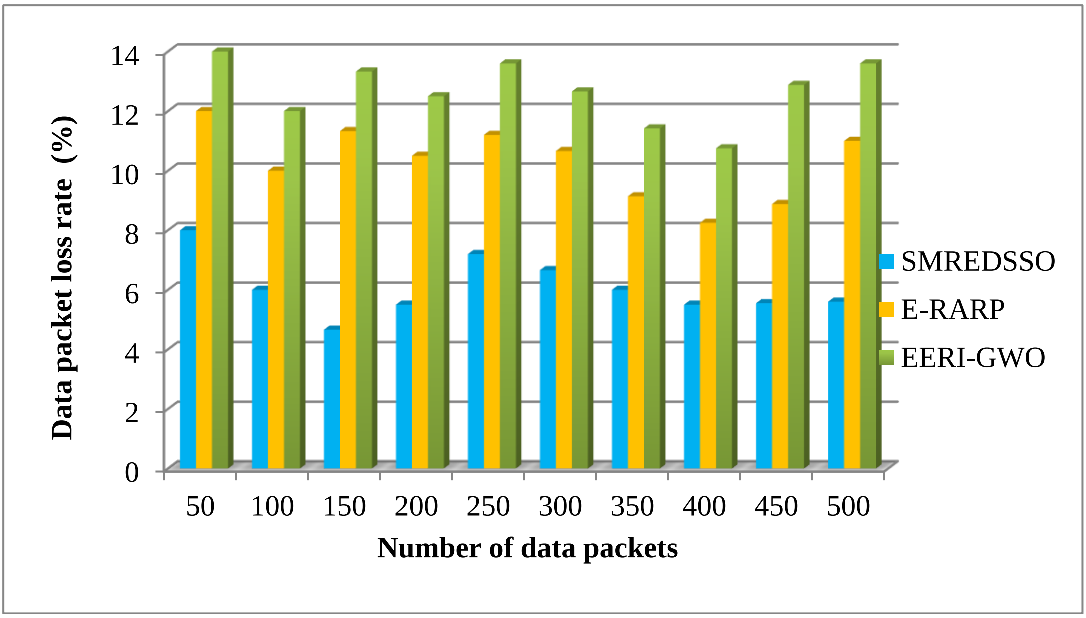

Figure 5 performance results of data packet loss rate

The comparative analysis of the data packet loss rate is depicted in Figure 5. To measure the performance of the SMREDSSO technique in terms of data packet loss rate, the number of data packets in the range of 50-500 was considered. During the simulation with 50 data packets in the first iteration, the proposed SMREDSSO technique [1] [2] lost 4, 6, and 7 data packets, respectively. As a result, the data packet loss rates for the SMREDSSO technique [1] [2] were observed to be 8%, 12%, and 14%, respectively. These results were compared to existing methods. The overall comparison results indicate that the data packet loss rate of the SMREDSSO technique is significantly minimized by 41% compared to [1] and 52% compared to [2]. This is because of selection of bandwidth-efficient sensor nodes using Wilcoxon signed-statistical repeated median regression analysis. The proposed optimization technique identifies better connectivity between the sensor nodes, leading to improved data delivery and minimized packet loss.

Table 5 Comparative analysis of delay

Number of data packets	Delay (ms)		
	SMREDSSO	E-RARP	EERI-GWO
50	12	14	15
100	14	16.5	17.5
150	16.5	18.2	20
200	21	23	25
250	23.3	25	27
300	25.1	27	30
350	27	30	32
400	28.5	32	34
450	29.3	33	36
500	31.2	34	37

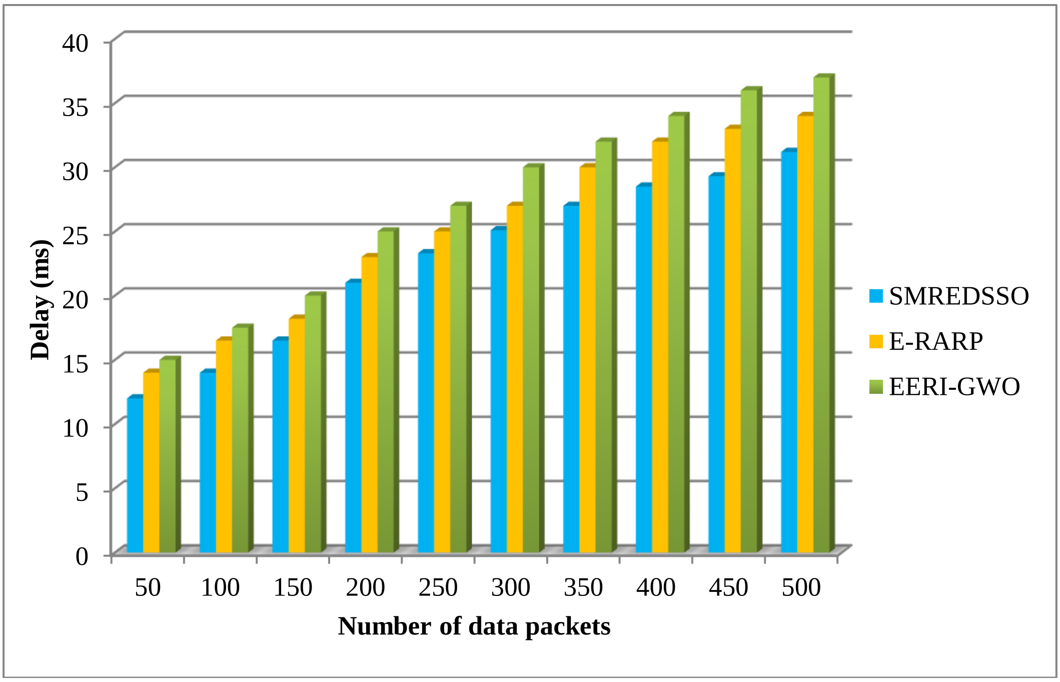

Figure 6 performance results of delay

Figure 6 illustrates the impact of delay versus the number of data packets, ranging from 50 to

500. As depicted in the graphical outcome above, the delay increases for all three methods with an increasing number of data packets. However, the proposed SMREDSSO technique exhibits a lower delay, ensuring accurate data transmission for forest fire detection. For instance, considering '50' data packets sent from the source node, the delay of the SMREDSSO technique was measured to be ′12ms,' while the delays for existing methods [1] and [2] were '14ms' and '15ms,' respectively. This mathematical result demonstrates that the SMREDSSO technique outperforms others in minimizing delay. The overall evaluation results confirm that the delay in delivering data packets is significantly reduced by 10% compared to [1] and 17% compared to [2]. The notable improvement is achieved through the identification of energy- and bandwidth-efficient nodes for data forwarding by the SMREDSSO technique. Additionally, the technique determines the next hop node through an Elitist Divergencive Squirrel Search Optimization, discovering an efficient path between sensor nodes for data forwarding. This minimizes the delay in data delivery at the base station, thereby reducing forest fire detection time.

6. CONCLUSION

Data forwarding is essential for WSNs to deliver data packets to their destinations. In a forest fire detection application, sensors are deployed to monitor environmental conditions and events. In this paper, the SMREDSSO technique is proposed for energy-efficient data forwarding in WSNs. The regression analysis in the proposed SMREDSSO technique determines the efficient node with better energy and bandwidth to enhance network lifetime and minimize packet loss. Following this, data forwarding is performed using the Elitist Divergent Squirrel Search Optimization method. This process helps improve data delivery and minimizes delay. A comprehensive simulation is carried out with a forest fire dataset to collect forest environmental information, and performance evaluation is conducted using metrics such as energy consumption, data packet delivery ratio, data packet loss rate, and delay. The results presented in this paper demonstrate that the SMREDSSO technique improves energy-efficient data forwarding in WSNs, achieving a higher delivery ratio and minimum loss as well as delay compared to existing methods.

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