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Research Article

Revolutionizing Wireless Sensor Networks through an Effective Approach for Quality of Service Enhancement

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ABSTRACT

Data Collection of Wireless Sensor Networks (WSN) are integral parts of modern technology in various fields. Nonetheless, due to inherent limitations like energy, bandwidth, and computation, a prominent challenge that arises is providing Quality of service (QoS). WSNs consist of constrained resource networks of sensors (e.g., batteries); thus, routing and deployment techniques are significant for improving the QoS performance of WSNs. We have introduced a new method of High Secure Parallel Particle Swarm Routing Algorithm (HS-PPSRA) in this work to enhance the QoS in WSNs. The approach with the metrics is delta, hypervolume (HV), Result of Multi-objectives via Dynamic Weighting (RMDW), Non-Dominated Solution (NDS) concerning important data transfer, dynamic change of network features, and using adaptive routing algorithms. Results show significant improvements in QoS metrics including reduced latency, increased reliability, and energy utilization. For checking existing algorithms, the proposed HS-PPSRA outperforms past algorithms. This case resolves the issues associated with QoS enhancement and presents a holistic approach to transitioning WSNs.

1. INTRODUCTION

With the advances of wireless sensor networks(WSNs), these applications are now integrated on the market such as healthcare, disaster management, smart environments, etc. Nevertheless, they are hampered by issues like energy constraints, time-varying network conditions, and the requirement for improved Quality of Service (QoS). Inspired by the significant impact of WSNs in present-day technology, this research aims to develop High-Secure Parallel Particle Swarm Routing Algorithm (HS-PPSRA) to encounter those challenges. QoS optimization encompasses the improvement of QoS metrics with the help of dynamic routing and adaptive paradigms, the main goals being reduction in latency, enhancement of reliability, maximization of available energy. The significance of this study is its potential impact on transforming the performance and scalability of WSNs across various applications. Interest in wireless sensor networks has increased in both the research and industry sectors since the year 2000. A wireless sensor network (WSN) is a set of nodes that work together to detect and possibly affect the environment around them. People and computers may interact with their surroundings via a WSN [1]. WSNs can create new applications and probable markets, yet they also expose some restrictions on design that need to develop new paradigms Developers. Detecting, processing, and communicating while using limited energy spurs a cross-layer design approach that usually necessitates taking medium access control, communication protocols, and distributed signal/data processing into account simultaneously [2].WSNs have been employed in many different applications;

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including disaster management, smart homes, smart manufacturing, healthcare, and environment monitoring.Large numbers of resource-constrained sensor or actuator nodes, or simply nodes, are present in WSNs [3]. Nodes in the network can connect to share data. In addition to its ability to work each node's function as a relay or data fusion node primary responsibility is to monitor the surroundings using the onboard sensors. Every node can function as a router, transmitting neighbor data to the Base Station (BS) or sink. BS can be used as a local data processor or as the network gateway to send data to distant computers [4].Transmission of messages to accomplish a specified message throughput (quantity of service) and QoS is the fundamental problem in communication networks. QoScan be expressed in terms of bit error rates, packet loss, transmission power, economic cost of transmission, message delay, and due dates [5]. There are a few common network topologies that can be employed, depending on the application, QoS, installation environment, and cost factors. Nodes, which are the building blocks of a communication network, are computers that can send and receive messages via cable, wireless sensors, or communication connections. One of the most used methods for managing the topology of WSNs and enhancing network performance is clustering [6]. By using a set of pre-established criteria, such as providing QoS, optimizing resource usage, network load balancing, etc. Clustering groupings nodes into units referred to clusters. Every cluster is made up of a Cluster Head (CH) or more, who gather data from members and communicate the combined data to BS either in a direct and indirect manner through intermediate nodes [7]. In this study, we discuss the transforming WSNs with an efficient method for improving QoS.

1.1 Contribution of the study

- The development of HS-PPSRA introduces a novel routing algorithm tailored for WSNs.
- The primary focus of HS-PPSRA is to improve the overall QoS in WSNs.
- Using the approaches such as RMDW, HV, delta and NDS, the algorithm tackles the intricate problems of few resources and fluctuating network circumstances in WSNs.

WSNs are becoming the fundamental building block that enables modern developments in technology regarding real-time accumulation and pervasive monitoring in smart environments, from healthcare to disaster management. As a matter of fact, being intrinsically limited by restricted energy, bandwidth, and computational capability, they raise significant challenges as far as QoS guaranteeing is an issue. Application-specific QoS is indispensable and needs to be enhanced in these WSNs for better performance in applications. Motivated by these constraints and the critical role that WSNs play in supporting vital applications, this research, therefore, tries to overcome the weaknesses of the existing methods of QoS optimization by presenting a new routing algorithm. Over the years, many methods have been tried in an attempt to achieve QoS optimization in WSNs. Protocols like ACC, among other hierarchical routing schemes, have demonstrated traditional energy efficiency with enhanced connectivity. As an example, PSO was performed for sensor deployment and cooperation to execute a common task, presenting good results under particular conditions. Similarly, clustering-based techniques, such as the Black Widow Optimization technique and PSO, are also supported by Fuzzy Logic that so far has been playing a prime role in enhancing network lifetime with load balancing in energy consumption. However, most of them suffer from scalability issues and are less effective in dynamic environments. Some of the recent innovations in this direction include environment-fusion multipath routing protocols, advanced clustering algorithms integrated with fitness functions for the optimal selection of cluster heads. Despite these advances, most of the existing techniques are not very effective in handling the trade-offs between conflicting QoS objectives such as coverage, latency, and energy usage. Besides, most of the techniques lack strong mechanisms in handling fluctuating network conditions or safeguarding data. In the backdrop of these lacunae, this study is presenting the High-Secure Parallel Particle Swarm Routing Algorithm (HSPPSRA) aimed at the dynamic optimization of QoS metrics for efficient utilization and adaptability in heterogeneous WSNs.

2. LITERATURE REVIEW

The study [8] suggested the Adaptive Coverage and Connectivity (ACC) strategy to achieve an effective WSN model. It uses two fundamental methodologies: the first assures the coverage rate and offers the most effective exposure to target items based on a mathematical model. The network's energy usage and connection are addressed by the second technique. The study [9] employed two enhanced iterations of the sensor deployment problem addressed by the Particle Swarm Optimization (PSO) technique. Cooperative PSO is the first, while fuzzy logic is used in the second to improve cooperative PSO. The study [10] provided an investigation of energy-efficient hierarchical routing systems using swarm intelligence and classical methods. The study [11] utilized genetic algorithms by including the variables of residual energy, proximity to the sink, and node density into its developed fitness function, the optimum Clustering protocol is intended for optimum CH selection. The study [12] proposed the “cluster-based routing protocol for information-centric wireless sensor networks (CBR-ICWSN)” which is an Internet of Things (IoT) enabled. The ideal collection of CHs is effectively selected by using a clustering approach based on black widow optimization (BWO) to the proposed model.

The study [13] represented a message-forwarding service that is capable of withstanding tough conditions with environment-fusion multipath routing protocol (EFMRP). Routing choices in EFMRP are based on a combination of potential fields that take the environment, residual energy, and depth into consideration. The study [14] investigated a revolutionary cooperative image processing technique for WSN that operates from the device that transmits to the receiver. For WSN, they developed techniques for a multi-hop, a one-way delayed collaborative communication paradigm. They think that improved picture transmission efficiency is a result of cooperative communication. The study [15] suggested a novel neighborhood indexing sequence (NIS) technique for WSN data compression. The proposed NIS technique therefore assigns dynamically less complex code words for every letter of the input sequence by exploiting the presence of neighbors. Study [16] provided an air quality measurement method with a WSN made up of a dispersed sensor network coupled with a cloud system.

3. METHODOLOGY

This section illustrates an efficient methodology for improving QoS in WSNs. Thus, it introduces the most important and relevant topics for the core principles of the study.
The proposed High-Secure Parallel Particle Swarm Routing Algorithm (HS-PPSRA) improves the QoS in WSNs by optimizing energy usage, reducing latency, and improving reliability using dynamic routing and clustering mechanisms. Based on the PPSO framework, the algorithm partitions the network into regions using mathematical partitioning based on fitness functions, such as energy consumption, node distribution, and task completion efficiency. It uses parameters such as total energy consumption, a number of cluster heads, and node distribution for calculating the fitness value of particles. This helps in efficient clustering. The theoretical background involves the utilization of particle movement equations for updating position and velocity, which helps in convergence to optimal solutions. The major steps are initializing the positions and velocities of the particles, clustering the nodes based on the fitness values, iterative updates in order to refine the clustering process, and segmentation of the network to optimal clusters. All the parameters such as learning coefficients, weight factors, and numbers of iterations have been carefully chosen by balancing between the exploration and exploitation, which prevents early convergence and ensures the robustness. This comprehensive approach hence ensures the scalability and reproducibility of the algorithm, making it suitable for dynamic WSN environments..

3.1 Quality of Service (QoS)

There is not generally accepted meaning of the term QoS, but it refers to the capability to provide the assurance that the service needs of applications are met. This insurance depends on the type of application targeted. To realize dependability, timeliness, robustness, availability, and security in WSNs, QoS may be recommended. The level of satisfaction with these services can be gauged using several QoS metrics, such as packet loss rate, jitter, throughput and latency. This study considers other aspects for a variety of applications, such as maximizing energy usage, coverage, and connection to assess QoS. A discrete collection of solutions gives rise to the Pareto Front, demonstrating that it is not possible to achieve more than one goal at a time without sacrificing others. The following objectives define the PF approach:

1. Convergence: To identify a group of Pareto optimal solutions that is related to one another.
2. Variability: To avoid early convergence and attain an even-handed trade-off PF, a collection of varied solutions has to be found. It should emphasize the symmetry of variety in two dimensions, but more challenging to accomplish in spatial three dimensions.

3.3 High-secure parallel particle swarm routing algorithm (HS-PPSRA)

Kennedy and Ehrhart (1995) introduced the intelligent algorithm known as the particle swarm optimization (PSO) method. It has been used in a variety of industries, including image processing, neural networks, mechanical design and communication. It can be used to improve network efficiency by addressing routing issues in WSNs. parallel particle swarm Optimization (PPSO) to determine the best task delegation strategy in WSNs. The energy distribution, task completion time, and energy use of the optimal overall performance are obtained by this method by taking into the proper fitness function's trade-off and the various indexes. The objective is to optimize the lifespan of heterogeneous WSNs by utilizing the PPSO method for sensor deployment and a scheduling heuristic. Sensor nodes are scheduled using the PPSO method once the ideal locations have been determined to reach the network lifespan theoretical upper bound. In comparison to the random deployment approach, this heuristic algorithm works better. Additionally, it can reduce energy usage and increase the lifetime of the network.
A normal sensor network comprises M clusters, which consists of N sensors. In each cluster, there are $[N/M]$ nodes on average. The PPSO technique is used to calculate the network region partition line, dividing the network into two halves.

$$K = (w, z, \theta_w, \theta_z) \tag{1}$$

where w, z is the point line segmentation's horizontal and vertical coordinates, θ_w is the angle that separates the line from the W axis, $and\ \theta_z$ represents the angle formed by the line and the W axis. In equation (2), the value of fitn ess $E\ of\ L$ particles are computed as follows:

$$E = \alpha \sqrt{\sum_{j=1}^{2}(d_j - e_j)^2} + \beta \sqrt{\sum_{j=1}^{2}\left(\frac{F_j}{D_j} - \frac{F_{sum}}{M}\right)^2}\ ,\ (\alpha + \beta = 1) \quad (2)$$

$$e_j = \frac{N_j}{N} \quad (3)$$

where $D_j (j = 1,2)$ is the quantity of nodes with sensors present in the region j, D_j is the region's total energy consumption j, and F_{sum} is the whole energy. N_j denotes the total number of cluster leaders across the network. This is the clustering method explained:

Step 1: Every sensor node in the network broadcasts its position, energy and other status data, among other things, to the base station.

Step 2: The PPSO technique is used to cluster the whole network following the base station gets the message, and L particles are determined.

Step 3: Particle factors $(w, z, \theta_w, \theta_z)$ are assigned at random. Equation (1) is used to establish the region partition line. This means that there are $2L$ distinct sub-regions inside the total sensor network. Given that the nodes' locations are known, equation (2) can be used to get each node's matching E values.

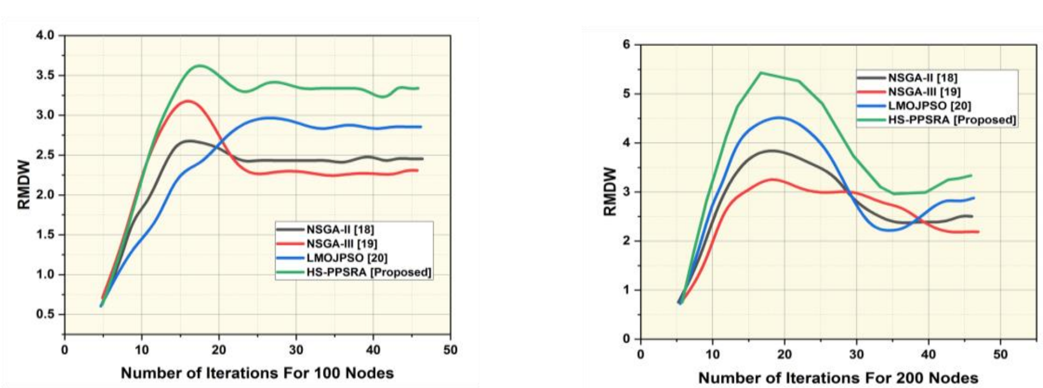
Step 4: Every sensor will validate the information above L varying fitness levels, and then contrast the lowest fitness found with the recent search outcome. Lastly, the lowest value ρ_{hc} is gained. The global extreme value can be derived from its associated particles. Similarly, the highest fitness value attained by an individual particle is considered the singular extreme value ρ_{jc}. Then updated $(w, z, \theta_w, \theta_z)$ the following equations take values into consideration.

$$\begin{aligned} W_{wid}(s+1) &= W_{wid}(s) + U_{wid}(s) \\ W_{zid}(s+1) &= W_{zid}(s) + U_{zid}(s) \\ W_{\theta,id}(s+1) &= W_{\theta_w,id}(s) + U_{\theta_w,id}(s) \\ W_{\theta_z,id}(s+1) &= W_{\theta_z,id}(s) + U_{\theta_z,id}(s) \end{aligned} \quad (4)$$

where W_{wid} and W_{zid} signifythe location of the particles, $W_{\theta_w,id}$ and $W_{\theta_z,id}$ are the dividing line's angle.

$$\begin{aligned} U_{wid}(s+1) &= \omega U_{wid}(s) + D_1 \times rand() \times [\rho_{id}(s) - W_{wid}(s)] + D_2 \times rand() \times [\rho_{hc}(s) - W_{wid}(s)] \\ U_{zid}(s+1) &= \omega U_{zid}(s) + D_1 \times rand() \times [\rho_{id}(s) - W_{zid}(s)] + D_2 \times rand() \times [\rho_{hc}(s) - W_{zid}(s)] \\ U_{\theta_{wid}}(s+1) &= \omega U_{\theta_{wid}}(s) + D_1 \times rand() \times \left[\rho_{id}(s) - W_{\theta_{wid}}(s)\right] + D_2 \times rand() \times \left[\rho_{hc}(s) - W_{\theta_{wid}}(s)\right] \\ U_{\theta_{wid}}(s+1) &= \omega U_{\theta_{wid}}(s) + D_1 \times rand() \times \left[\rho_{id}(s) - W_{\theta_{wid}}(s)\right] + D_2 \times rand() \times \left[\rho_{hc}(s) - W_{\theta_{wid}}(s)\right] \end{aligned} \quad (5)$$

where D_1 and D_2 are two elements of learning, ω is a factor of weight, and s is the quantity of repetitions.



(a) (b)

Fig. 1. The RMDW and varying iteration counts (a) 100 sensor (b) 200 sensor

Step 5: Particles are renewed $(w, z, \theta_w, \theta_z)$quantities to update the equation (1). After that, Step 3 is reached iteratively until the fitness value Eapproaches the lowest possible value.

Step 6: The two subregions are split again when the region is segmented, till the final$M$Clusters emerge. Algorithm 1 shows the process of HS-PPSRA.

Algorithm 1: Pseudocode for HS-PPSRA

Stage 1*: [Stage of Initialization]*
For (*y =0 to the quantity of people or solutions)*
For *(M =0 to the quantity of nodes for sensors).*
Decisions are chosen at random. Use the answer to calculate a new path.
End For
Determine the initialized solution's fitness value. Determine the local and global best.
End For
Stage 2*: [Update stage] when the conditions are not compatible*
For *(y =1 to quantity of solutions)*
For *(m =1 to the number of nodes ofthe sensor)*
The PPSO update equation is used to update the solution.Create a new route by utilizing the updated solution.
End For
Determine the fitness value of the modified route. Determine the local and global best.
End For

The experiment in this paper is conducted using a fabricated dataset to test the performance of the proposed HS-PPSRA. This dataset contains sensor nodes and sinks nodes distributed in a two-dimensional plane with predefined dimensions. There are 200 sensor nodes tested by running the algorithm for 2 iterations, such as 25 and 50. The fabricated dataset has simulated realistic WSN deployment scenarios with a focus on energy consumption, task execution, and dynamic conditions of the network. For evaluating the performance of HS-PPSRA, three important metrics have been used, namely hypervolume (HV), delta, and Non-Dominated Solutions (NDS). HV reflects the diversity and distribution that HS-PPSRA gets regarding QoS objectives; the higher the value of HV, the better the trade-off optimization. Delta assesses the uniformity and spreads that solutions have got in the Pareto front; the lower the value of delta, the better the consistency and distribution it has. NDS characterizes the solutions dominating others in all objectives without any compromise and represents the quality of optimization. These metrics provide a comprehensive framework to analyze the algorithm's performance in balancing conflicting QoS parameters. The experimental setup guarantees robustness, interpretability, and relevance of the results to real-world WSN applications.

4. RESULTS AND DISCUSSION

In this section, we have discussed an efficient method for improving the QoS in WSNs. The Intel Core TM i7-9700K, 2.4 GHz CPU, Windows 10 operating system and 8GB of RAM were used in the experiment. The proposed method compared the existing methods are Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [18],Non-dominated Sorting Genetic Algorithm-III(NSGA-III) [19], and lagged multi-objective jumping particle swarm optimization (LMOJPSO) [20]. xperimental results demonstrate that the proposed HS-PPSRA outperforms other state-of-the-art algorithms such as NSGA-II, NSGA-III, and LMOJPSO regarding the important QoS metrics such as hypervolume (HV), delta, and NDS. For most cases, HS-PPSRA has a higher HV, meaning a better optimization of the trade-off with wider distribution of the solutions, especially with increased iterations and for 200 sensor nodes. The smaller values of delta ensure that solutions obtained with HS-PPSRA are more uniform and consistent, hence more reliable optimized QoS. Moreover, the algorithm generates more NDS, which further justifies its capability to handle several conflicting objectives, such as energy efficiency and latency, without compromising on solution quality. These results can be attributed to HS-PPSRA's dynamic clustering mechanism and its use of parallel particle swarm optimization to adaptively balance network conditions and resource constraints. Enhanced performance has specific implications for existing technologies in that it provides more efficient and scalable solutions for WSN applications. It addresses critical limitations of earlier algorithms, such as poor adaptability to dynamic network environments and suboptimal energy use. However, the higher computational complexity of the algorithm may limit its application in low-resource scenarios. However, the results reflect that HS-PPSRA is highly suitable for applications requiring robust and reliable QoS, such as IoT-enabled systems, health care monitoring, or disaster management networks.

4.1 Dataset

The suggested approach is carried out using a fabricated dataset [17]. The sink nodes and sensors that are positioned on the identical 2-dimentional plane with dimensions of $D_x X D_y$ indicate the attributes of this dataset. The dataset contains 500 sensor nodes and 4 iterations. We have used in this study 200 sensor nodes and 2 iterations like 25 and 50.

4.2 Evaluation metrics

The most popular assessment metrics are delta, HV, and quantity of additional NDS indicators are employed in this study.A various number of situations and iterations are tested for each method. The same hold for varying iteration counts, such as 25 and 50. These tests are conducted again with varying numbers of sensor nodes distributed in the interest area (100, and 200). The outcomes of each method are also influenced by computation times. Thus, to prevent temporal complexity for the suggested technique, calculation time has been included and assigned a weight. The computed outcomes for RMDW, where HS-PPSRA outperforms other techniques are displayed in Figure 1. This result indicates that even with the computing time added to the combination model, HS-PPSRA could better the other techniques. Table 1 displays the average values of NDS, Delta, and HV for 100 and 200 sensors using 25 and 50 iterations of the proposed and existing methods.

TABLE I. THE MEAN VALUE FOR DELTA, NDS, AND HYPERVOLUME

Method	**Average of HV 100 Sensors**		**Average of HV200 Sensors**	
	25 iterations	**50 iterations**	**25 iterations**	**50 iterations**
NSGA-II [18]	4	5	7	6
NSGA-III [19]	3	4.2	4	5.5
LMOJPSO [20]	1	0.5	2.5	8
HS-PPSRA [Proposed]	9	14	7.5	9.2
	Average of NDS 100 Sensors		**Average of NDS 200 Sensors**	
	25 iterations	**50 iterations**	**25 iterations**	**50 iterations**
NSGA-II [18]	9	12	8.2	9
NSGA-III [19]	8	10	6.4	8.4
LMOJPSO [20]	11	11	10.9	11
HS-PPSRA [Proposed]	12	13	11.5	9.8
	Average of delta 100 Sensors		**Average of delta 200 Sensors**	
	25 iterations	**50 iterations**	**25 iterations**	**50 iterations**
NSGA-II [18]	2.3	2.5	5.5	4.6
NSGA-III [19]	3	2.9	7.5	4
LMOJPSO [20]	0.7	0.7	1	2
HS-PPSRA [Proposed]	3.4	3.4	4.2	4.7

Experimental results clearly show that the proposed HS-PPSRA outperforms other algorithms, including NSGA-II, NSGA-III, and LMOJPSO, in several significant QoS metrics like hypervolume (HV), delta, and nondominated solutions. Higher HV values of HS-PPSRA in most scenarios mean a better trade-off optimization with a wider solution distribution in 200 sensor nodes with higher iteration counts. The lower values of delta further confirm that HS-PPSRA yields solutions with more uniformity and consistency, hence a reliable QoS optimization. Besides, the algorithm generated more NDS, confirming its strength in handling multi-conflicting objectives such as energy efficiency and latency without compromising on the quality of the solution. These results are attributed to the dynamic clustering mechanism of HS-PPSRA and parallel particle swarm optimization used for adapting the network conditions to resource constraints adaptively. Better performance has certain implications for existing technologies in providing more efficient and scalable solutions for WSN applications. It addresses some critical limitations of earlier algorithms, including poor adaptability to dynamic network environments and suboptimal energy use. However, the higher computational complexity of the algorithm may restrict its application in low-resource scenarios. Results are in fact indicating that the HS-PPSRA would highly serve applications which do require robust and reliable QoS: IoT-enabled systems, healthcare monitoring, and disaster management networks.

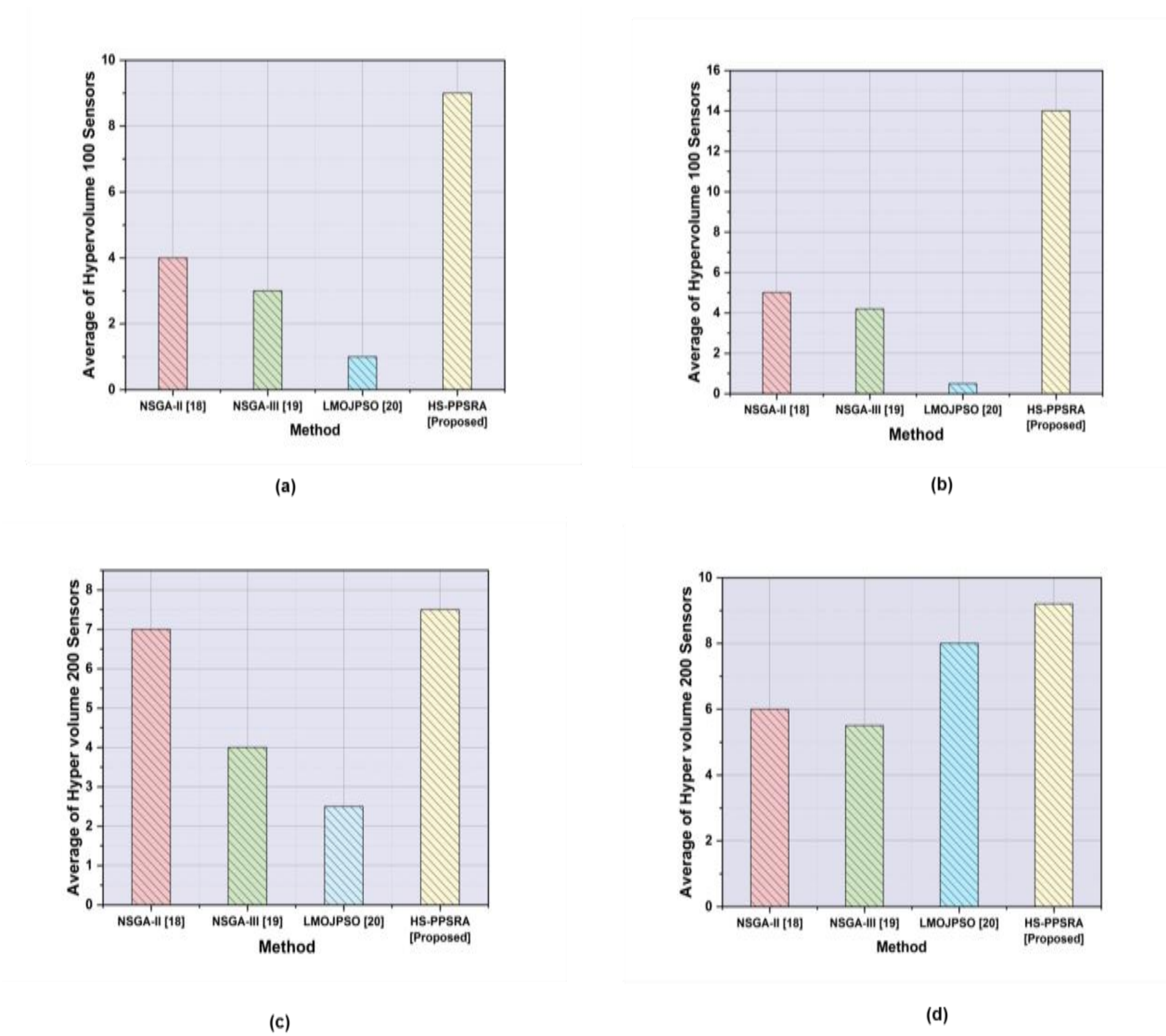


Fig. 2. Mean of HV (a) 100 sensors using 25 iteration (b) 50 iteration using 100 sensor (c) 200 sensors using 25 iterations (d) 50 iterations using 200 sensors

The hypervolume parameter is a metric used in algorithm assessment for WSNs to determine the level of quality of the technique's generated solutions. In the context of WSNs and QoS requirements, an increased hypervolume denotes a greater distribution and coverage of solutions, demonstrating the algorithm's capacity to successfully balance trade-offs among many objectives. A user-defined reference point and a restricted space by the PF are needed for computation.The average assessment of the HV indication for the techniques utilized is shown in Figure 2. The HV indication for 100 nodes is displayed in the first row using 25, and 50 iterations. The HV for 200 nodes is displayed in the second row with the same number of iterations as the first row.

The Delta (Δ) indicator is used to evaluate variety within the set by examining the spread and distribution of a collection of solutions. The meaning of the sequential distances and the Euclidean spacing between successive solutions are then computed. Since this signal indicates a uniform distribution, these values need to be minimized as much as possible. It measures the improvement or difference between different solutions produced by the algorithm, focusing special attention on the way each solution affects the QoS parameters [21-31]. Researchers can evaluate the efficacy of algorithms in improving QoS metrics by using the Delta parameter, which provides important information about the algorithm's efficiency and potential to improve WSN functionality. The mean assessment of the Delta for 100, and 200 sensors, respectively, is shown in Figure 3.

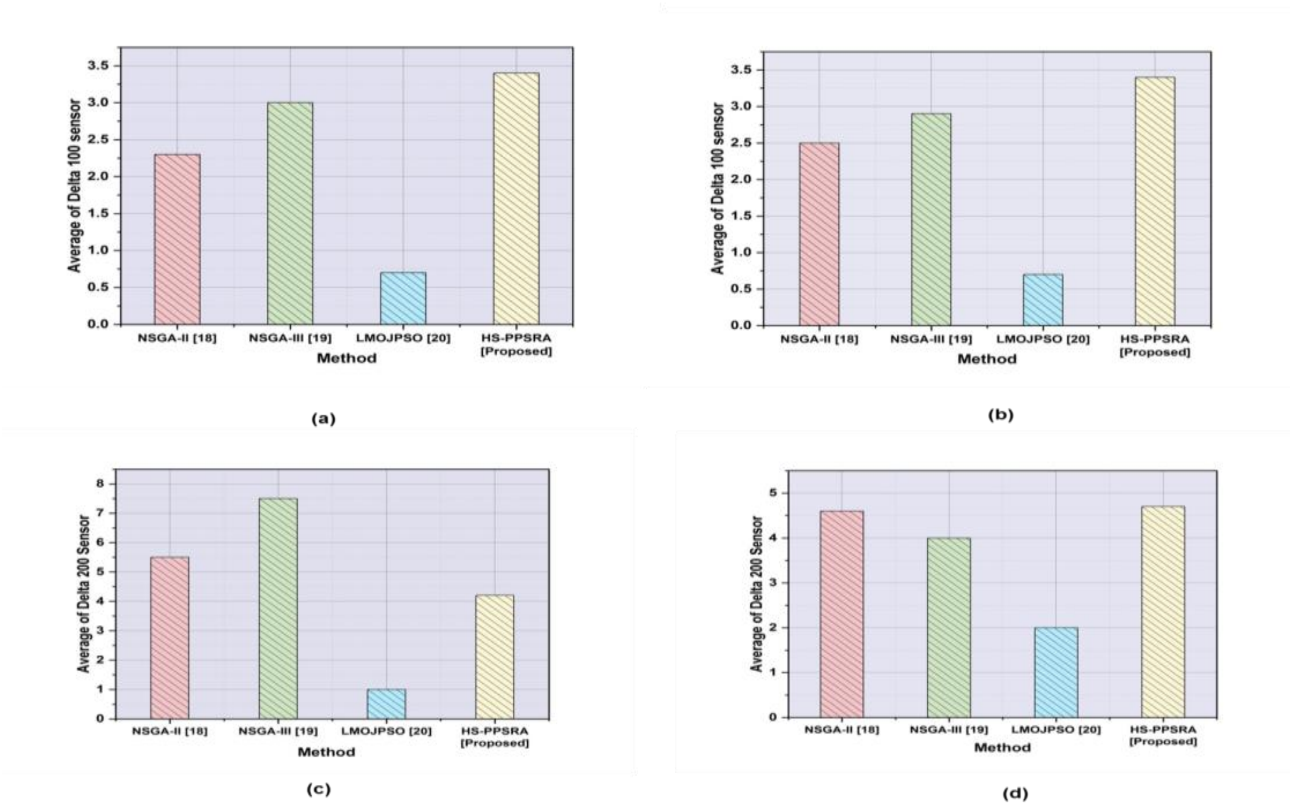


Fig 3. Mean of delta (a) 100 sensors using 25 iteration (b)50 iteration using 100 sensor (c) 200 sensors using 25 iterations (d) 50 iterations using 200 sensors.

The NDS parameter is used to identify solutions that outperform other solutions in all stated objectives. An NDS is a solution that cannot be enhanced to achieve one goal without compromising another [32-37]. NDS solutions are essential for optimization because they represent the trade-offs between many QoS metrics in WSNs and form the PF. These technologies support decision-making processes for WSN installations and algorithm creation by helping to discover the best trade-offs.The average evaluation of the NDS indication for each row's 100, and 200 nodes is shown in Figure 4. The average values for the 100 and 200 sensing devices for the suggested and current approaches are shown in Table 2.

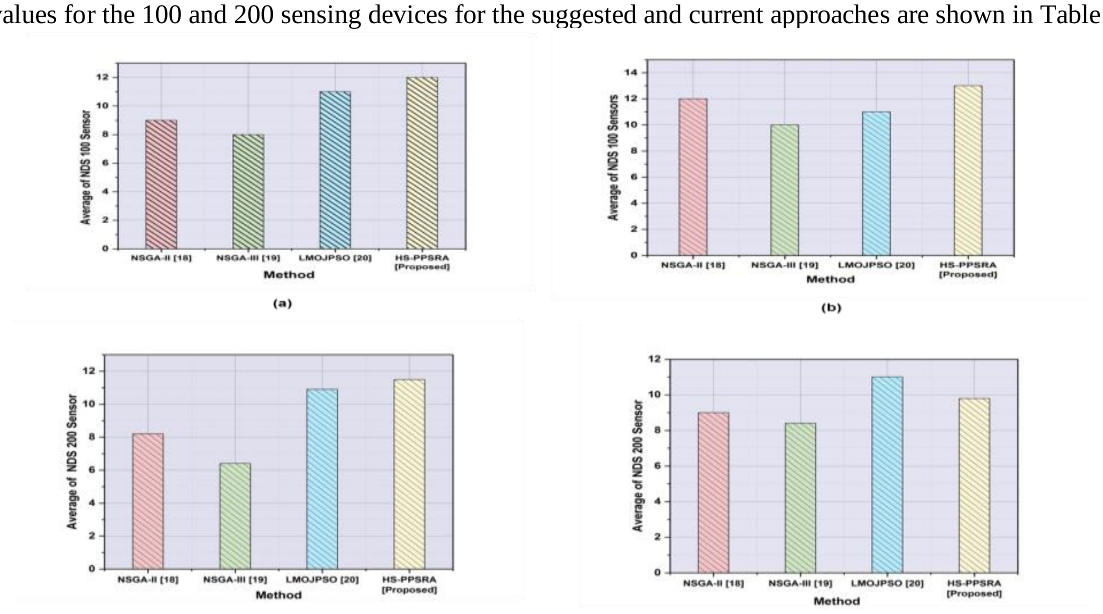


Fig. 4. Mean of NDS (a) 100 sensors using 25 iteration (b)50 iteration using 100 sensor (c) 200 sensors using 25 iterations (d) 50 iterations using 200 sensors

TABLE II. PERCENTAGE OF QOS MODEL OF THE PROPOSED AND EXISTING METHODS

Methods	100 sensors	200 sensors	Average (%)
NSGA-II [18]	23%	22%	22.5%
NSGA-III [19]	25%	26%	25.5%
LMOJPSO [20]	21%	24%	22.5%
HS-PPSRA [Proposed]	30%	34%	32%

Comparative studies have illustrated that the proposed HS-PPSRA outperforms all other methods with respect to major QoS metrics, such as hypervolume HV, NDS, and delta values. HS-PPSRA has higher HV in all cases, which represents better solution distribution and space coverage, and produces more NDS, leading to superior optimization of QoS objectives. Main reasons for its higher performance include dynamic clustering, adaptive routing capabilities, and an effective utilization of the particle swarm optimization to balance energy consumption and network efficiency. However, due to the iterative nature of it, with complex computations in the fitness functions, it is computationally expensive and hence may not be applicable in resource-constrained environments. Its advantages are scalability, robustness in dynamic network conditions, and the ability to optimize multiple conflicting objectives; hence, it is suitable for applications like disaster management, healthcare monitoring, and IoT-enabled smart environments. On the other hand, higher computational complexity and fine-tuning parameters are some of the limitations that may not be appropriate in real-time scenarios. Overall, HS-PPSRA represents a significant advancement in WSN QoS optimization, offering versatile applications where reliability and efficiency are critical.

5. CONCLUSION

The proposed research introduces the High-Secure Parallel Particle Swarm Routing Algorithm as an innovative solution for improving QoS in WSN. The contribution focuses on the key challenges of energy efficiency, latency reduction, and improvement in reliability by applying advanced clustering mechanisms and parallel particle swarm optimization techniques. The algorithm adapts dynamically to the conditions of the network, optimizes resource distribution, and improves network performance based on multiple QoS metrics. The comparison with existing methods-NSGA-II, NSGA-III, and LMOJPSO-justify the superiority of HSPPSRA to give higher hypervolume, more NDS, and lower delta values, which signify better trade-off optimization with consistency in solutions. The novelty in this research is the combination of adaptive routing with robust clustering to address the limitations of conventional WSN algorithms. This work further improves the state-of-the-art in WSN QoS optimization and paves the way for practical applications in dynamic IoT-enabled systems, disaster management, and healthcare monitoring. With its scalable and effective platform, HS-PPSRA contributes significantly to developing intelligent and dependable WSN technologies by addressing the present challenges and raising further inspiration for future developments.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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