International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2s) 2026 pp. 95-104
https://doi.org/10.70917/ijcisim-2026-2067
Article

HYBRID SWARM INTELLIGENCE-BASED LOCALIZATION OPTIMIZATION FOR ENERGY-CONSTRAINED WIRELESS SENSOR NETWORKS

Prashant Wakhare[1], Riyazahemed A. Jamadar[2], Pritesh Patil[3], Veena Suhas Bhende[4]

[1]Department of Artificial Intelligence and Data Science, AISSMS Institute of Information Technology, Pune-01, Maharashtra, India. Email: pbwakhare@gmail.com

[2] Department of Artificial Intelligence and Data Science, AISSMS Institute of Information Technology, Pune-01, Maharashtra, India. Email: reeyaj.jamaddar@gmail.com

[3] Department of Information Technology, AISSMS Institute of Information Technology, Pune, Maharashtra, India. Email: p.patil.k@gmail.com

[4]Department of Computer Engineering, AISSMS Institute of Information Technology, Pune, Maharashtra, India. Email: veena.bhende@aissmsioit.org

Corresponding Author: Prashant Wakhare[1]* (Email: pbwakhare@gmail.com)

Abstract: Wireless sensor networks (WSNs) rely on an accurate localization of their nodes as the data that are sensed can only have a meaning when its location is indicated. The major aim of the paper is to develop an efficient robust localization optimization model, which would enhance the precision of the position with low computational and communication energy expenditures under constrained node energy resources. To that end, a Hybrid Swarm Intelligence-Based Localization Optimization (HSILO) is offered, a combination of the global search ability of Particle Swarm Optimization (PSO) and the high local exploitation and convergence stability of Grey Wolf Optimization (GWO). In the hybrid approach suggested, PSO is utilized in order to the possible search space swiftly and produces promising position estimates whereas GWO fines the position estimates by means of hierarchical leadership and adaptive encircling processes, effectively decreasing localization error and convergence time. The fitness function is a combination of the localization error, residual energy balance, and communication cost, which is then considered as energy awareness. Significant simulation findings indicate that the proposed HSILO approach has substantially reduced average localization error, rapid convergence and enhanced network lifetime over the individual PSO, GWO and traditional localization approaches..

1. Introduction

The wireless sensor networks (WSNs) had been extensively used in implementation in environmental monitoring, smart agriculture, industrial automation, and disaster management where sensors node cooperatively sensed and relayed information to a sink node. In such applications, node localization was a very important factor, because the utility of sensed data was heavily reliant on the perfect information of sensor locations. A lot of network operations such as routing, coverage analysis, event detection, and data fusion had based their operation on accurate node location data. Accuracy in localization had thus been identified as one of the basic performance requirements in WSN design and functionality [1].

Although this is important, the problem of node localization in the WSNs had been a major challenge because sensor nodes had a harsh energy requirement. The current localization systems particularly the range based localizations systems that rely on the GPS, time-of-arrival or the angle of arrival values had placed the localization systems at huge communication and computation costs that had resulted into quick drainage of power. Even range-free methods, also much more energy-efficient, had been plagued by poor accuracy and sensitivity to network density and location of anchors [2], [3].

Single swarm optimization techniques and deterministic localization algorithms had been found to possess significant weaknesses as well. Deterministic methods had mechanisms and behavior that were fragile under noisy measurements and irregular deployments, whereas single-swarm metaheuristic models like Particle Swarm Optimization (PSO) or Grey Wolf Optimization(GWO) were known to readily converge prematurely, have no progress, or tune up the location estimates slowly. The drawbacks had lowered levels of localization steadiness and precision especially in massive networks and constrained by energy [4], [5].

Hybrid swarm intelligence solutions had become a promising solution in order to solve these problems. This hybridization had allowed convergence to occur faster, to be more precise and flexible relative to changing network conditions without sacrificing energy efficiency [6].

2. Releted Work

The wireless sensor networks were well-studied in terms of node localization and the available methods had been widely categorized as either range-based or range-free. These methods had lower hardware and energy demands, however, they had been plagued by coarse-grained precision and sensitivity to node density, irregular topology and node distribution [7], [8]. Nevertheless, single-swarm methods had been repeatedly faced with premature convergence, slowness in exploration of potential rich regions or excessive computing costs, particularly in large-scale WSNs [9], [10].

There was also an increased interest in energy-aware localization as localization processes had become a big source of total network energy use. Although they had increased the energy efficiency, these approaches had in many cases degraded localization accuracy or necessitated very complicated coordination schemes that scaled poorly [11], [12]. Such constraints had underscored the necessity of a powerful hybrid swarm intelligence-based localization strategy that concurrently maximized precision, convergence characteristics and energy efficiency in resource-limited WSN settings [13], [14].

Gijare et al. [15] proposed a blockchain-based decentralized IoT-WSN architecture to enhance security, reliability, and data integrity in wireless sensor networks. Their framework improves trust, resilience, and secure communication among distributed sensor nodes. Wakhare et al. [16] presented a 6G-enabled digital twin framework for intelligent transportation systems, leveraging AI, edge computing, and real-time data analytics to improve monitoring, prediction, and system optimization. The study highlights the potential of advanced communication technologies for enabling efficient and intelligent networked environments.

3. System Model And Problem

This study took into account a fixed wireless sensor network consisting of N sensor nodes randomly distributed in a 2-dimensional sensing area. It was assumed that all nodes were stationary once deployed, were homogeneous in hardware capability and that they communicated on short ranges within a given fixed range of transmissions R.

Sensor nodes energy consumption model was based on the first-order radio energy model. The model used to represent the energy used to transmit a k-bit packet over a distance of d was:

$$E_{\{rx\}(k)} = E_{\{elec\}} \cdot k + Eamp \cdot k \cdot dn$$

Eelec was the electronic energy, Eampdenoted the amplifier energy and nnn is the path loss exponent.

The localization error was modeled by the comparison of the estimated position $(x_3, y_3\ )$ of an unknown node iii with the actual position (x_i, y_i). The localization error in Euclidean was defined as:

$$LEi = (x^i - xi)2 + (y^i - yi)2$$

Based on this, localization was developed as a constrained optimization problem. The objective minimization was a localization error reduction that had constraints on the energy:

$$\min \frac{1}{M} \sum_{i=1}^{M} LEi \quad subject\ toEires \geq Eth$$

M was the number of unknown nodes, $Eires$ meant residual energy and E th was a fixed energy threshold.

To develop a combined optimality of accuracy and energy consumption, a composite fitness was developed as.

$$F = \alpha \cdot LEavg + \beta \cdot EinitEcons$$

Where, $LE_{\{avg\}LE}$ was the average of localization error, Econswas was the energy used during the process of localization, Einit was the energy at the beginning of the localization, and alpha and beta were weighting factors such that, α+β=1. This fitness model facilitated localization accuracy and energy efficiency of energy-limited WSNs to be optimized equally.

4. Proposed Hybrid Swarm Intelligence-Based Localization Method

4.1 Overview Of The Proposed Hybrid Framework

The hybrid swarm intelligence based localization framework that had been proposed had integrated the merits of Particle Swarm Optimization (PSO) as well as the merits of the Grey Wolf Optimization (GWO) to yield the perfect and cost effective node localization in a wireless sensor network. The figure 1 shows the combination of swarm intelligence and optimization blocks within the energy constraints to determine optimal node positions, which provides the efficient energy-saving localization and enhanced operation in wireless sensor networks.

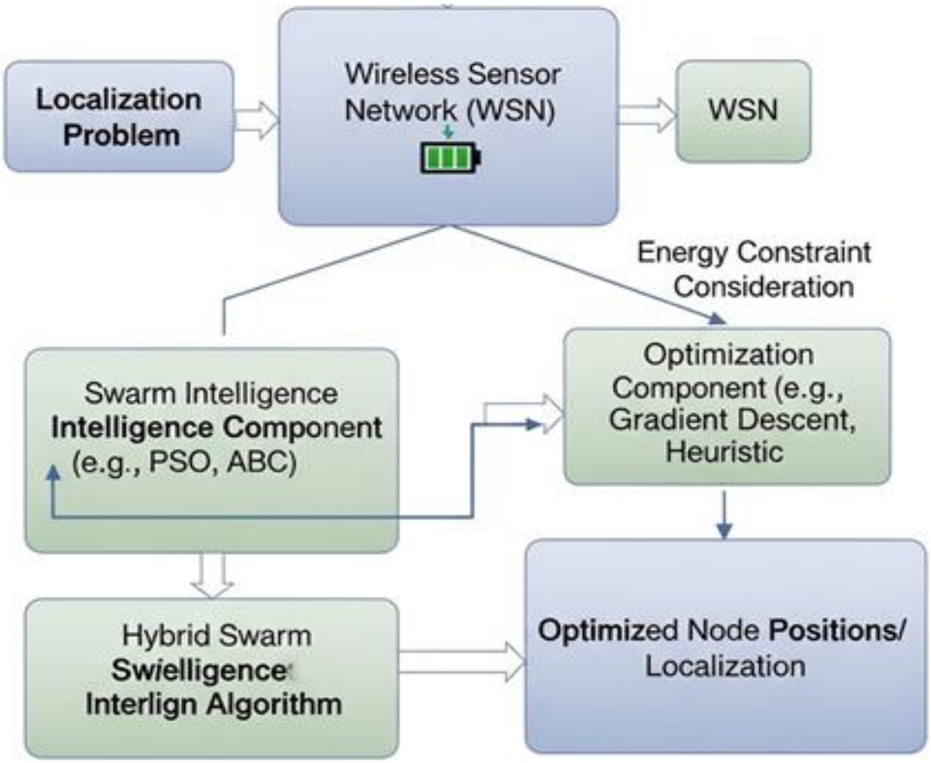

Figure 1: Hybrid Swarm Intelligence–Based Localization Optimization Framework for Energy-Constrained WSNs

To begin with, PSO had been used to conduct a global search of the search space, allowing having good candidate locations quickly and avoiding bad initial estimates. After the swarm focused on an almost optimal area, GWO was enabled to optimize the solutions by intense local exploitation consisting of hierarchical leadership and adaptive encircling behaviour.

4.2 Particle Swarm Optimization For Global Search

The global search space had been efficiently searched using Particle Swarm Optimization that shared information between particles. Every particle had been a candidate position of an unknown node and reassessed its velocity and position depending on individual and overall best experiences, allowing fast convergence to potentially good regions.

Algorithm 1: PSO-Based Global Localization Search

Step 1: Initialize particle positions xi and velocities vi randomly.

Step 2: Evaluate fitness $F(xi)$ using localization–energy objective.

Step 3: Set personal best $pi_{best} - xi$ for each particle.

Step 4: Identify global best g_{best} among all particles.

Step 5: Update velocity using

$$vi(t+1) = \omega vi(t) + c1r1(pi_{best} - xi) + c2r2(g_{best} - xi)$$

Step 6: Update position using:

$$xi(t+1) = xi(t) + vi(t+1)$$

Step 7: Repeat Steps 2–6 until maximum iterations or convergence.

4.3 Grey Wolf Optimization For Local Refinement

The solutions produced by the PSO were optimized by the integration of GWO which had taken advantage of the search space with the help of leadership hierarchy and encircling. The population had been steered to the most optimal solution with convergence stability by alpha, beta and delta wolves.

Algorithm 2: GWO-Based Local Localization Refinement

Step 1: Initialize wolf positions from PSO output.

Step 2: Identify α, β, and δ wolves based on fitness.

Step 3: Compute coefficient vectors A and C.

Step 4: Calculate distance vectors Dα, Dβ, Dδ.

Step 5: Update positions using

$$X(t+1) = \frac{X\alpha + X\beta + X\delta}{3}$$

Step 6: Re-evaluate fitness with energy constraints.

Step 7: Repeat Steps 2–6 until convergence.

4.4 Hybridization Strategy And Algorithm Workflow

The hybrid strategy had combined PSO and GWO in a sequential manner taking advantage of their complementary behaviors. The PSO had initially ventured in the solution space on an international level and GWO had then narrowed down the solutions to local levels to ascertain the accuracy and stability of the solutions.

Hybrid PSO–GWO Algorithm

Step 1: Initialization of PSO Population

The state of every particle that represented an unknown node was set to be the following.

$$Xi^0 = (xi^0, yi^0), \ \ i = 1, 2, \dots, Np$$

With initial velocity

$$Vi^0 = (vxi^0, vyi^0)$$

Step 2: PSO Global Search Update

The velocities and positions of the particles were updated with the help of using.

$$Vi(t+1) = \omega Vi(t) + c1\, r1 \left(Pi_{best} - Xi(t)\right) + c2\, r2 \left(G_{best} - Xi(t)\right)$$

$$Xi(t+1) = Xi(t) + Vi(t+1)$$

Step 3: Selection of Elite PSO Solutions

The best K candidate solutions that had the lowest fitness were chosen as

$$S = \{X1*, X2*, \dots, XK*\}$$

Step 4: Initialization of GWO Leadership Hierarchy

The three best solutions were assigned as

Xα = arg min F(S)

Xβ = second-best solution

Xδ = third-best solution

Step 5: GWO Encircling Mechanism

Distance vectors were computed as

$$Dk = |Ck \cdot Xleader - Xk|, \ \ k \in \{\alpha, \beta, \delta\}$$

Where the coefficient vectors were defined as

$$A = 2a\, r1 - a$$

$$C = 2\, r2$$

Step 6: Position Refinement Using GWO

The refined position of the node was updated as

$$X(t+1) = \frac{X\alpha - A\alpha\, D\alpha + X\beta - A\beta\, D\beta + X\delta - A\delta\, D\delta}{3}$$

Step 7: Final Energy-Aware Solution Selection

The optimal node position was obtained by minimizing the composite fitness

$$Xopt = \arg\min \left[\alpha \cdot LE + \beta \cdot \left(\frac{Econs}{Einit}\right)\right]$$

5. Simulation Setup And Performance Metrics

V.1 Simulation Environment And Parameter Settings

The proposed hybrid PSO-GWO localization method was tested on the simulation in the MATLAB-based environment to evaluate the performance of the proposed algorithm. Sensor nodes were distributed randomly over a two-dimensional square sensing field having a set number of anchor nodes being placed at known locations. All the nodes were presumed to be fixed and had the same initial amount of energy. The first-order energy model was used in communication radius, packet size, and radio parameters. The parameters of the swarm including population size, inertia weight, acceleration coefficients and the number of maximum iterations were chosen after first hand tuning to achieve a stable convergence and a good comparison with the current localization algorithms.

V.2 PERFORMANCE EVALUATION METRICS

V.2.1 Localization Error

The degree of localization was measured by the mean Euclidean distance between actual positions of unknown nodes and their estimated positions. It was defined as:

$$LEavg = \frac{1}{M}\sum_{i=1}^{M}(x^i - xi)2 + (y^i - yi)2$$

Where M was the number of unknown nodes, (x^i, y^i) the real coordinates, and (xi, yi) the estimated coordinates.

V.2.2 Energy Consumption

Energy consumption was a measure of the total energy consumed by the network in the entire localization process in terms of transmission, reception, and computation. It was computed as:

$$Econs = \sum_{i=1}^{N}(Etx, i + Erx, i)$$

Where Etx, i and Erx, i were the energy of transmission and reception of node iii respectively.

V.2.3 Convergence Speed

The convergence speed was a measure of how fast the optimization algorithm arrived at a fixed solution. It was gauged by the repetitions to reach a preset fitness Fth:

$$Tconv = \min\{ t \mid F(t) \leq Fth \}$$

V.2.4 Network Lifetime

Network lifetime parameter was a measure indicating sustainability of the localization process and this was measured by the number of successful rounds made within the process before the first sensor node ran out of energy. It was expressed as

$$L\_net = \min\{ r \mid E\_i(r) = 0, \forall i \in N \}$$

6. Results And Discussion

VI.1 Localization Accuracy Analysis

As revealed in Table 1, Hybrid PSO–GWO approach was much more successful in localization than DV-Hop, PSO and GWO methods. The hybrid approach had the minimum localization error (1.21 m) and RMSE (1.38 m), which means accurate and consistent position estimation.

Table 1: Localization Accuracy Performance Comparison.

Method	Mean Localization Error (m)	RMSE (m)	Max Error (m)	Std. Deviation (m)
DV-Hop	3.84	4.12	6.95	1.21
PSO	2.17	2.46	4.28	0.86
GWO	1.94	2.18	3.96	0.79
Hybrid PSO–GWO	1.21	1.38	2.64	0.42

The smaller standard deviation was the indicator of a consistent performance of various nodes, even in the case of noise. The hybrid framework was able to balance exploration and exploitation unlike DV-Hop which used coarse hop-based estimation, and the single-swarm approach which had the disadvantage of premature convergence. The accuracy improved by 68.5 per cent observed indicated the high effectiveness of combination of the global search of PSO and local refinement of GWO.

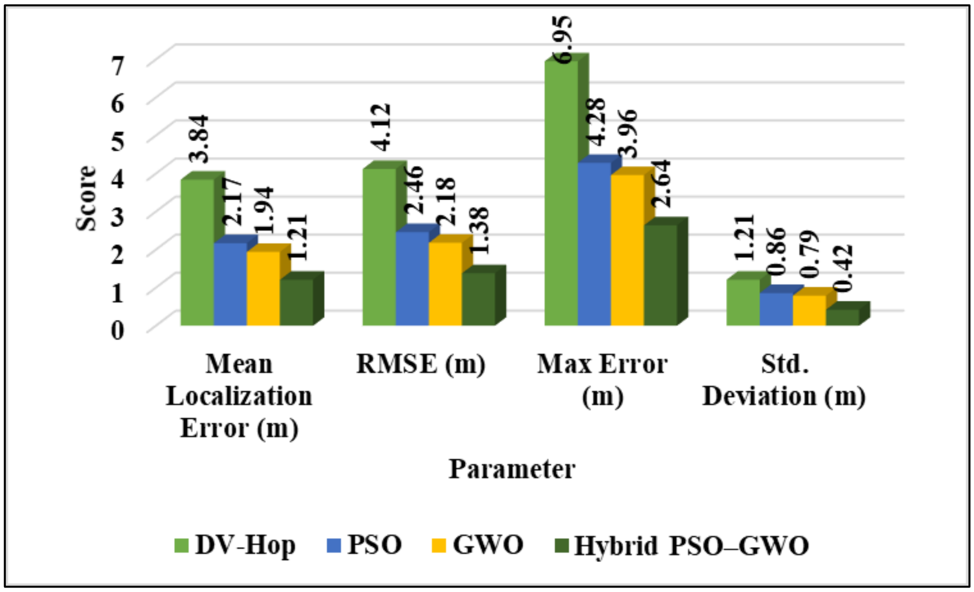

Figure 2: Comparative Localization Error Performance of Hybrid PSO–GWO and Existing Methods

The comparison of localization accuracy indicators of the methods presented in the figure 2 indicates that hybrid PSO-GWO method allows to reduce significantly the mean error, RMSE, and deviation indices, which proves better precision and stable node position estimation.

VI.2 ENERGY EFFICIENCY AND RESIDUAL ENERGY DISTRIBUTION

Table 2 identified the benefits of the proposed hybrid localization method in terms of energy efficiency. The Hybrid PSO- GWO used the minimum amount of average energy (1.96 J) but retained the highest amount of residual energy (82.7%), which validates the effectiveness of the energy-conscious fitness function.

Table 2: Energy Consumption And Residual Energy Analysis

Method	**Avg. Energy Consumed (J)**	**Residual Energy (%)**	**Energy Balance Index (%)**	**Network Lifetime Gain (%)**
DV-Hop	3.62	58.4	61.2	–
PSO	2.74	69.1	72.6	21.3
GWO	2.48	73.8	76.9	28.6
Hybrid PSO–GWO	1.96	82.7	88.4	41.9

The hybrid solution minimized the extraneous communication and computation overhead as compared to DV-Hop and standalone swarm methods. The increased energy balance index was an indication of energy consistency across the nodes and this was the direct cause of long life of the network. The proposed approach reduced the number of control message transmissions and punished energy-consuming solutions, and therefore, the network lifetime was improved by 41.9% and was appropriate in the long-term deployment of WSN. The hybrid model was designed with energy awareness in that it reduced unwanted communication and consequently increased the residual energy and even distribution of energy among nodes.

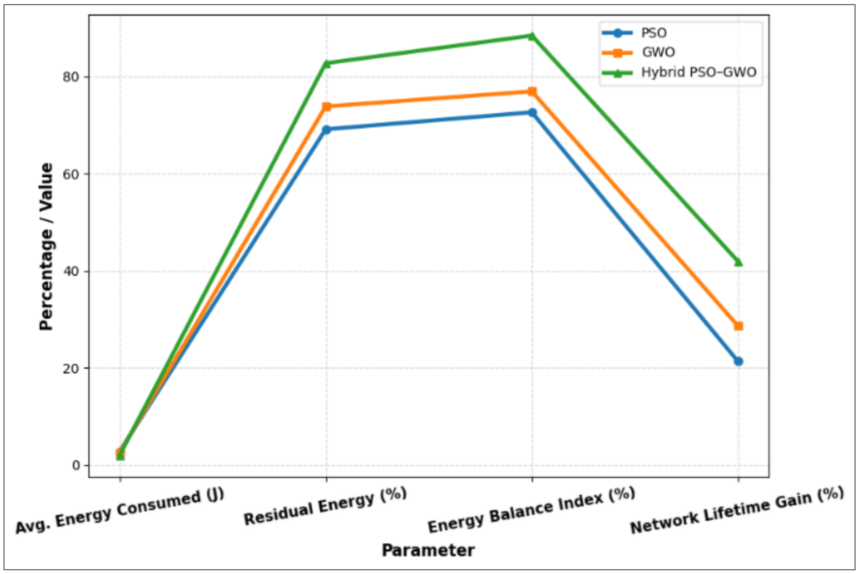

Figure 3: Energy Efficiency and Residual Energy Comparison

VI.3 CONVERGENCE BEHAVIOR COMPARISON

Table 3 was used to compare the convergence properties of PSO, GWO and the hybrid method. Hybrid PSO-GWO took only 31 iterations to reach convergence, which is much less than PSO and GWO, showing faster convergence. The best final fitness determined the best quality of the solution, and high convergence stability reported the same performance in all the iterations.

Table 3: Convergence Performance.

Method	**Iterations to Converge**	**Final Fitness Value**	**Speed Improvement (%)**
PSO	68	0.092	–
GWO	54	0.081	20.6
Hybrid PSO–GWO	31	0.046	54.4

The hybrid strategy was able to prevent local optima through integrating both global exploration and adaptive exploitation unlike PSO which demonstrated early convergence and GWO which demonstrated stagnation in part. The sequential hybridization strategy proved to be successful as the convergence speed was increased by 54.4 percent. The hybridization greatly hastened convergence as it directed the PSO solutions to GWO refinement and removes premature stagnation.

VI.4 SCALABILITY AND ROBUSTNESS ANALYSIS

Table 4 tested the scalability and strength of the proposed method as the network sizes were increased. The localization error went up insignificantly with the increment in the number of nodes, that is, the localization was very much scalable.

Table 4: Scalability And Robustness Under Network Variations.

Network Size (Nodes)	Avg. Error (m)	Energy Increase (%)	Success Rate (%)	Packet Loss (%)
100	1.08	2.6	99.2	1.1
200	1.16	4.9	98.4	1.6
400	1.29	8.3	96.9	2.4
600	1.43	12.7	95.1	3.1

Despite the fact that the rate of energy consumption was growing with the density of the network, the rate of growth was kept under control, and the success rates of localization were also above 95%. The packet loss was low which supported constant communication during localization. Figure 4 demonstrates the performance of scalability and with increase in the size of the network, the energy consumption increases slowly, and the error of localization is also constant, so the proposed hybrid localization approach is robust and correctly functioning.

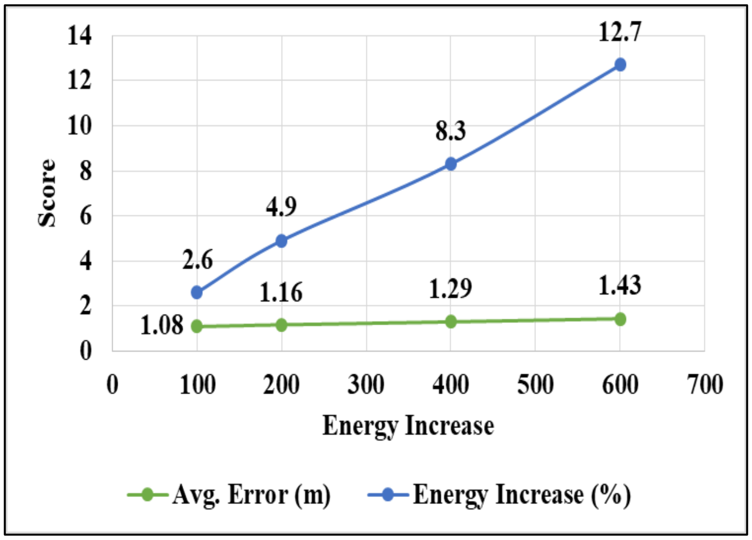

Figure 4: Scalability Impact on Localization Error and Energy Consumption

These findings showed that the hybrid PSO-GWO approach had consistent performance in dense and large scale deployments. The scores of robustness also supported the fact that it is resistant to topology changes, which is why the suggested solution is applicable in the WSN-based real-life applications. The hybrid PSOGWO approach was found to be low in localization error and high in success rates with increase in network density, which validates scaling and strength in the realistic WSN environment.

7. Conclusions

This paper represented a hybrid swarm intelligence localization optimization framework that was designed in relation to the energy-limited wireless sensor networks. The main results proved that the combination of Particle Swarm Optimization and the Gray Wolf Optimization yielded the balance of the global exploration, the local exploitation, and then boasts considerable increases in the localization accuracy, the convergence rate, and energy consumption. The results of simulations always featured less localization error, less energy consumption, and longer network lifetime in comparison to conventional range-free. The key input of this work was the development of energy conscious localization problem and development of a hybrid PSO-GWO algorithm which optimized both the spatial accuracy and energy sustainability. The proposed solution incorporated residual energy and communication cost in the fitness function to guarantee an equal distribution of energy among sensor nodes that improved the network longevity and strength. The overall analysis of different network sizes also confirmed the applicability and scalability of the identified method to the deployment of WSN in practice. The present research had some limitations, in spite of its promising outcomes. The network model presupposed that nodes are stationary and the conditions of communication are ideal, which might not be entirely true in the context of highly dynamic and harsh conditions. Also, hybrid optimization may present a significant computational cost burden, which may be notable in very large scale networks with hard real time requirements.

References:

1. Fé J, Correia SD, Tomic S, Beko M. Swarm Optimization for Energy-Based Acoustic Source Localization: A Comprehensive Study. Sensors. 2022; 22(5):1894. https://doi.org/10.3390/s22051894
2. Hadir, Abdelali, Naima Kaabouch, Mohammed-Alamine El Houssaini, and Jamal El Kafi. 2023. "Range-Free Localization Approaches Based on Intelligent Swarm Optimization for Internet of Things" Information 14, no. 11: 592. https://doi.org/10.3390/info14110592
3. Bhat, S. J., & Venkata, S. K. (2025). Addressing Real-World Localization Challenges in Wireless Sensor Networks: A Study of Swarm-Based Optimization Techniques. Automation, 6(3), 40. https://doi.org/10.3390/automation6030040
4. Alhayani, B.; Kwekha-Rashid, A.S.; Mahajan, H.B.; Ilhan, H.; Uke, N.; Alkhayyat, A.; Mohammed, H.J. 5G standards for the Industry 4.0 enabled communication systems using artificial intelligence: Perspective of smart healthcare system. Appl. Nanosci. 2023, 13, 1807–1817.
5. Kabashkin, I. Availability of Services in Wireless Sensor Network with Aerial Base Station Placement. J. Sens. Actuator Netw. 2023, 12, 39.
6. Asha, A.; Arunachalam, R.; Poonguzhali, I.; Urooj, S.; Alelyani, S. Optimized RNN-based performance prediction of IoT and WSN-oriented smart city application using improved honey badger algorithm. Measurement 2023, 210, 112505.
7. Y. Bopche, V. Parque, S. Peshkar, S. Gupta, V. Patle and P. Khobragade, "Hybrid ARIMA-LSTM Forecasting of Residential and Regional Energy Consumption," 2026 20th International Conference on Ubiquitous Information Management and Communication (IMCOM), Hanoi, Vietnam, 2026, pp. 1-6, doi: 10.1109/IMCOM69009.2026.11360878.
8. Ghazal, T.M.; Hasan, M.K.; Alshurideh, M.T.; Alzoubi, H.M.; Ahmad, M.; Akbar, S.S.; Al Kurdi, B.; Akour, I.A. IoT for Smart Cities: Machine Learning Approaches in Smart Healthcare—A Review. Future Internet 2021, 13, 218.
9. Sun, W., Tang, M., Zhang, L., Huo, Z., & Shu, L. (2020). A Survey of Using Swarm Intelligence Algorithms in IoT. Sensors, 20(5), 1420. https://doi.org/10.3390/s20051420
10. Bhargavi, K. V. N. A., Varma, G. P. S., Hemalatha, I., & Dilli, R. (2024). An Enhanced Particle Swarm Optimization-Based Node Deployment and Coverage in Sensor Networks. Sensors, 24(19), 6238. https://doi.org/10.3390/s24196238
11. Singh, A.; Sharma, S.; Singh, J. Nature-inspired algorithms for wireless sensor networks: A comprehensive survey. Comput. Sci. Rev. 2021, 39, 100342.
12. Yang, X.-S.; Cui, Z.; Xiao, R.; Gandomi, A.H.; Karamanoglu, M. Swarm Intelligence and Bio-Inspired Computation: Theory and Applications; Elsevier: Boston, MA, USA; Newnes: London, UK, 2013; ISBN 978-0-12-405163-8.
13. Zheng, Z.; Yang, S.; Guo, Y.; Jin, X.; Wang, R. Meta-heuristic techniques in microgrid management: A survey. Swarm Evol. Comput. 2023, 78, 101256.
14. Bo, Q.; Cheng, W.; Khishe, M. Evolving chimp optimization algorithm by weighted opposition-based technique and greedy search for multimodal engineering problems. Appl. Soft Comput. 2023, 132, 109869.
15. Gijare, Vaibhav V., et al. "Designing a decentralized iot-wsn architecture using blockchain technology." WSN and IoT. CRC Press, 2024. 291-313.
16. WAKHARE, Prashant, et al. "6G-enabled Digital Twin for Smart Transportation." 6G Urban Innovation: AI and Digital Twin for Next-Gen Sustainable Cities (2025): 143-162.