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A Comparative Analysis of Advanced Routing and Cluster Head Selection Algorithm Using Lagrange Interpolation

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Abstract: This paper presents a unified performance metric for evaluating the chronological wild geese optimization (CWGO) algorithm in wireless sensor networks (WSNs). The metric combines key performance factors—energy consumption, delay, distance, and trust—into a single measure using Lagrange interpolation, providing a more comprehensive assessment of WSN algorithms. We evaluate CWGO against E-CERP, EECHIGWO, DUCISCA, and DE-SEP across static and dynamic sensor node configurations in various wireless technologies, including LoRa, Wi-Fi, Zigbee, and Bluetooth low energy (BLE). The results show that CWGO consistently outperforms the other algorithms, especially in larger node configurations, demonstrating its scalability and robustness in static and dynamic environments. Moreover, the unified metric reveals significant performance gaps with EECHIGWO, which underperforms all wireless technologies. DUCISCA and DE-SEP show moderate and fluctuating results, underscoring their limitations in larger networks. While E-CERP performs competitively, it generally lags behind CWGO. The unified metric offers a holistic view of algorithm performance, conveying clearer comparisons across multiple factors. This study emphasized the importance of a unified evaluation approach for WSN algorithms and positions CWGO as a superior solution for efficient cluster head selection and routing optimization in diverse WSN scenarios. While CWGO demonstrates superior performance in simulation, future research should validate these findings in real-world deployments, accounting for hardware limitations and in a highly dynamic environment. Further optimization of the unified metrics' computational efficiency could enhance its real-time applicability in larger, energy-resource-constrained WSNs.

Keywords: chronological concept; optimization; wild geese migration optimization; wireless communication technologies; wireless sensor network; WSN routing

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1. Introduction

Rapid advancements in wireless communication, computational intelligence, and metaheuristic optimization algorithms have allowed efficient and scalable solutions for complex problems, particularly in wireless sensor networks (WSNs). WSNs consist of small, low-power sensor nodes that transmit and receive data wirelessly using a wireless communication technology. They are widely used across numerous domains, including smart agriculture, education, telemedicine, search and rescue operations, environmental monitoring, military applications, and commercial sectors, for their ability to give timely and accurate data collection, monitoring, and communication over large areas. They are valuable in scenarios where manual data acquisition is dangerous or impractical. The sensor nodes deployed in these areas can be either static or dynamic, depending on the application requirements and the specific area where they are used. Static WSNs are primarily employed in applications where nodes remain stationary after deployment. These networks are ideal for long-term monitoring of a specific target area, such as air and water quality monitoring, soil moisture monitoring in agriculture, structural health monitoring, surveillance, and perimeter security. On the other hand, dynamic WSNs consist of mobile sensor nodes capable of changing location over time after deployment. Typical scenarios for them include search and rescue operations, wildlife monitoring and tracking, vehicular networks, and intelligent transportation systems. These applications offer greater flexibility and adaptability, making them suitable for changing environments or requiring sensor nodes to follow moving objects, people, or conditions. In both modes of WSNs, the limited energy resources of the nodes are a critical consideration during design and implementation. WSNs must be optimized to maximize energy efficiency to avoid network failure and guarantee optimal performance.

One technique to achieve optimal WSN performance is using cluster-based routing protocols that can be implemented in various methods. One of the most famous clustering protocols that pioneers this concept is the low-energy adaptive clustering hierarchy (LEACH) protocol [1]. This protocol works by randomly selecting a CH from the sensor nodes, and the selected CH transmits the data coming from the cluster members to the base station. The problem with the LEACH protocol is the randomness of CH selection. It may select a CH with low residual energy or nodes at the edge of the WSN, making the transmission distance longer, which translates to more significant energy consumption.

The literature also proposes variations of the LEACH protocol to improve its performance, such as the LEACH-C [2], in which they incorporated a sorting algorithm to select the nodes with the highest residual energy as the best candidate to be the CH. By selecting nodes with higher residual energy as CHs, LEACH-C addresses some of the energy inefficiencies in the original LEACH protocol. However, as mentioned, this approach assumes a uniform distribution of nodes, which is not always the case in practical WSN deployments. In real-world applications, sensor nodes are often deployed in non-uniform, unpredictable patterns, making LEACH-C's assumptions less applicable and potentially leading to inefficient cluster formation and energy consumption in irregular deployments.

Another hierarchical routing protocol like LEACH is the base-station-controlled dynamic clustering protocol (BCDCP) [3], which utilizes the base station to perform energy-intensive computations such as the CH selection and routing that reduces the work allocations to individual sensor nodes. BCDCP also uses a minimum spanning tree algorithm to minimize energy consumption during inter-cluster communications, making it a more energy-efficient technique than the classical LEACH protocol. Despite these advantages, BCDCP's centralized structure introduces a significant vulnerability: the base station becomes a single point of failure. The entire network's operation is jeopardized if the base station malfunctions or is compromised. This limitation is particularly concerning in critical applications such as military or disaster recovery, where network reliability is paramount.

The common issue with classic clustering protocols in WSN is finding an optimal solution to achieve uniform energy consumption across the sensor nodes. To overcome this, recent research has turned to metaheuristic algorithms for CH selection and routing optimization in WSN. Metaheuristics such as the genetic algorithm (GA) [4,5], particle swarm optimization (PSO) [6,7], ant colony optimization [8], gray wolf optimization [9,10], firefly optimization [11,12], wild geese optimization algorithms [13], and their respective variations offer flexibility, scalability, and superior search capabilities. These algorithms are particularly well suited for dynamic and large-scale WSN environments. Unlike traditional deterministic approaches, metaheuristics can explore the solution space more thoroughly, thereby improving the chances of finding an optimal or near-optimal solution for energy-efficient clustering and routing. They have become popular due to their flexibility, scalability, and searchability in finding the optimal solution to many engineering problems, such as in WSN.

Similar advanced routing protocols and cluster head selection algorithms based on metaheuristic algorithms have also been proposed in the literature to achieve optimal WSN performance [13–26]. For instance, in [14–16,19,21,26], different optimization techniques were proposed by improving existing optimization algorithms such as the gray wolf optimization, sine-cosine algorithm, ant swarm foraging algorithm, or incorporating factors such as distance in the selection of cluster heads to improve the energy efficiency of WSNs. For instance, the algorithm proposed in [14] called EECHIGWO successfully improved the stability, energy efficiency, and stability of the WSN, but their approach was ineffective for heterogeneous nodes. The DUCISCA method proposed in [15] successfully reduced the overhead of nodes, effectively minimizing energy consumption, but their method had a higher death speed for the sensor nodes. The DE-SEP technique introduced in [19] was also successful in improving the death rate of each node and equally effective in improving energy efficiency as the WSN size increased. Still, their method suffered from degraded stability as the separation between the CH and other nodes and base station members increased. Lastly, the E-CERP method in [21] optimized the routing path, resulting in reliable communication between nodes, but in their study, only static nodes were considered. Aside from these limitations, these methods failed to incorporate other performance metrics like trust, delay, and distance in their evaluation. These different metrics are critical in ensuring the overall network reliability and efficiency. Furthermore, they are primarily designed for static sensor networks, limiting their applicability to dynamic environments where sensor nodes can move. Other papers in the literature [14–17,19–26] also failed to evaluate their research across different wireless technologies. They primarily optimize energy efficiency and cluster head selection but do not consider performance across wireless technologies like Bluetooth, Wi-Fi, LoRa, and ZigBee. Limiting their assessment to a single wireless entity diminishes its relevance for broader WSN applications and implementations.

Our previous research utilized the chronological wild geese optimization (CWGO) algorithm [13], which optimally selects routing paths and cluster heads in a WSN. We evaluated the CWGO algorithm against E-CERP, EECHIGWO, DUCISCA, and DE-SEP based on distance, delay, trust, and energy metrics. However, these comparisons focus solely on static sensor nodes and assess individual metrics rather than a unified measure of overall network performance. The literature lacks a comprehensive criterion that considers multiple factors. This study addresses these gaps by developing a unified performance metric using Lagrange interpolation, combining components such as distance, delay, trust, and energy into a single measure. The primary contribution of this research includes the following:

- Unified Performance Metric: A single performance metric developed using Lagrange interpolation integrates multiple factors, such as energy, delay, distance, and trust. This metric will comprehensively evaluate the performance of CWGO and other algorithms with various rounds and sensor node configurations.
- Evaluation Across Wireless Technologies and Node Configurations: This study builds on our previous research by comparing the proposed CWGO algorithm to others, such as E-CERP, EECHIGWO, DUCISCA, and DE-SEP, both bot static and dynamic sensor nodes for different wireless communication technologies (Wi-Fi, Zigbee, LoRa, and BLE).

The remainder of this paper is organized as follows: Section 2 introduces the proposed algorithm and evaluation method. Section 3 shows simulation results, Section 4 discusses these results in detail, and Section 5 concludes the study with recommendations for further improvement.

2. Materials and Methods

2.1. WSN Simulation Setup

We adopt a similar WSN simulation setup from our previous work [13], in which multiple sensor nodes are randomly dispersed in a designated area. These nodes sense, process, and transmit data via cluster heads to a sink node or base station. A total of n nodes in the WSN are grouped into clusters denoted C_i, each associated with a cluster head (CH) labeled ${H^i}_z$. For this paper, we utilized the K-means clustering algorithm to group the sensor nodes into clusters. K-means assigns nodes to clusters based on proximity, which helps minimize intra-cluster variance and enhances energy efficiency in data transmission.

Data from each sensor node is aggregated at the cluster head and then routed to the sink node or BS through a CH-based routing technique. This approach extends the WSN lifespan by minimizing energy consumption through optimal CH selection and routing path optimization. The CH selection and routing path are dynamically adjusted using our proposed chronological wild geese migration optimization (CWGO) algorithm [13] and other comparison algorithms for efficient energy use, minimal delay, and reliable transmission. Figure 1 illustrates the WSN system model. In this WSN system model, sensor nodes are organized into clusters labeled Cluster 1 to Cluster 5. Each cluster has one designated cluster head (CH) in which all the data from its cluster members are being transmitted. The CHs then transmit this consolidated data to the BS using a single-hop or multi-hop data transmission through the CHs in the WSN.

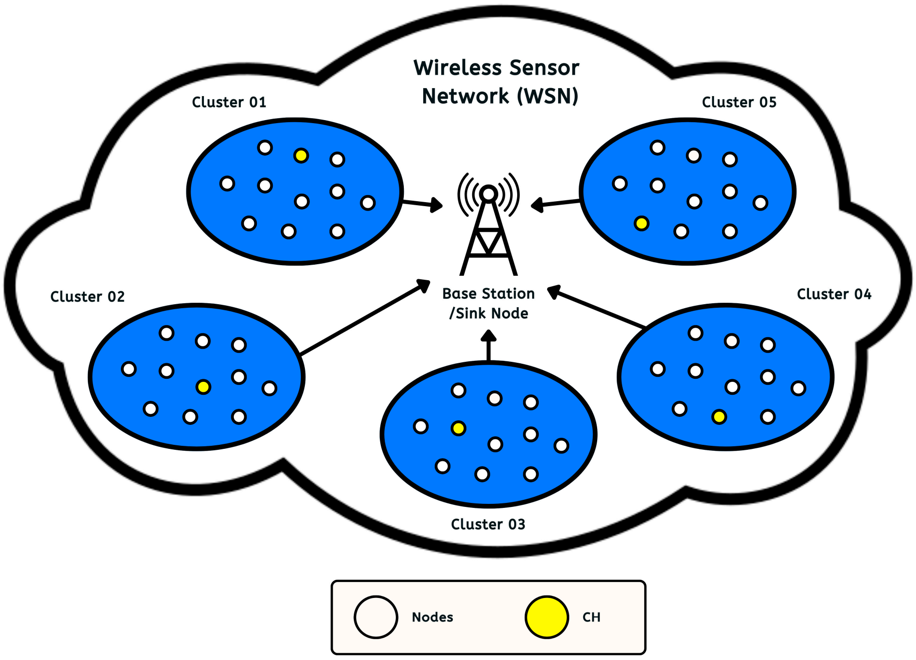

Figure 1. The WSN system model.

In this study, five different algorithms for CH and routing path optimization, namely DE-SEP, E-CERP, DUCISCA, EECHIGWO, and the proposed CWGO, were compared and integrated into the WSN simulation. Table 1 summarizes the detailed parameter settings for each algorithm, ensuring consistency across all simulation scenarios. These detailed configurations allow for a fair comparison of each algorithm's performance and facilitate reproducibility.

Table 1. Simulation parameters and settings.

Parameter	Proposed CWGO	DE-SEP	E-CERP	DUCISCA	EECHIGWO
Population Size	5	5	5	Randomly initialized, evolves over generations	10 solutions iterate over epochs
Iterations/Epochs	Adaptive with synchronized flight, foraging	Max 100	Max 10	Generational Evolution	10
Penalty for Low Energy Nodes	Excludes node with energy < 0.2	Excludes node with energy < 0.2	Excludes node with energy < 0.2	Excludes node with energy < 0.2	Excludes node with energy < 0.2

Table 1. *Cont.*

Parameter	Proposed CWGO	DE-SEP	E-CERP	DUCISCA	EECHIGWO
Clustering Technique	K-Means	K-Means	K-Means	K-Means	K-Means
Data Packet Size	Random varies between 1 and 10 per round	Random varies between 1 and 10 per round	Random varies between 1 and 10 per round	Random varies between 1 and 10 per round	Random varies between 1 and 10 per round

2.1.1. Static and Dynamic WSN Simulation

This paper investigates the performance of our proposed CWGO algorithm with static and dynamic sensor nodes through simulation. This approach helps determine whether our technique can perform well in stable and dynamic environments.

In the static WSN simulation, sensor nodes are randomly deployed within a predefined area. Once deployed, the nodes remain stationary throughout the simulation. This scenario reflects real-world applications where sensor nodes are fixed in place. Each node is assigned to a specific cluster, with one node per cluster serving as the CH responsible for aggregating data cluster members and transmitting it to the sink node or base station. Selecting CHs is critical for optimizing energy consumption as it has higher energy demands due to data processing and long-range transmission tasks. In the static simulation, the CWGO and algorithms, like E-CERP, EECHIGWO, DUCISCA, and DE-SEP, dynamically select the optimal CH based on several factors. This process minimizes energy dissipation across the network, extending its lifespan.

In dynamic WSN scenarios, mobility becomes a significant factor for applications like wildfire tracking, mobile healthcare, and intelligent transportation systems, where sensor nodes either move or must be redeployed due to environmental or operation changes. Our sensor node's positions are updated at the start of each simulation round to simulate mobility. This dynamic movement requires optimization to adapt their CH selection and routing strategies for each round. In addition, the nature of networks complicates the task of maintaining balanced energy distribution. As sensor nodes move, some nodes must transmit data over long distances, which increases energy consumption. At the end of each static and dynamic simulation scenario, the total distance traveled during the transmission of data by each node is calculated. The distance is calculated based on the value of the intra-cluster and inter-cluster distance presented in Equations (1) and (2), respectively:

$$\delta_1 = \frac{1}{\beta_1 mn} \sum\nolimits_{r=1}^{m} \sum\nolimits_{s=1-\neq s}^{n} l_{rs} \tag{1}$$

$$\delta_2 = \frac{1}{\beta_2 n} \sum\nolimits_{s=1}^{n} \sum\nolimits_{e=1}^{n} l_{se} \tag{2}$$

where

l_{rs} is the distance between rth and sth CHs;
β_1 and β_2 represents the normalization constant/factor;
δ_1 is the intra-cluster distance;
m is the node count;
n is the CH count;
δ_2 is the inter-cluster distance;
l_{se} is the distance between sth and eth CHs.

The transmission delay, expressed in Equation (3), is also calculated. It represents the time the data packet travels from node e to the CHs:

$$\vartheta = \sum\nolimits_{i=1}^{n} \frac{A_i}{m} \tag{3}$$

where

A_i refers to the node count in the ith CH;
m is the node count;
n is the CH count;
ϑ represents the delay in seconds.

Three kinds of trust, such as direct (DT), indirect (IT), and error-based (ET) trust, are also calculated to determine the trustworthiness of each node in the network. Each trust value is calculated using Equations (4)–(6) for the DT, IT, and ET. The average of the three trust values then represents the overall trust of the network.

$$DT_r^s(t) = \frac{1}{3}[DT_r^s(t-1) - \left(\frac{t_{approx} - t_{ant}}{t_{approx}}\right) + \rho] \tag{4}$$

$$IT_r^s(t) = \frac{1}{d}\sum\nolimits_{j=1}^{d} DT_j^s(t) \tag{5}$$

$$ET_r^s(t) = \frac{1}{K} * \sum\nolimits_{j=1}^{K} ET_j \tag{6}$$

where

r and s represents the node number;
t refers to the time in seconds;
t_{ant} and t_{approx} are the anticipated and approximated time required for authentication;
ρ specifies the node's witness factor;
DT is the direct trust;
d is the number of neighboring nodes between nodes r and s;
IT is the indirect trust;
ET_j is the error in the jth transmission;
K represents the number of transmission;
${ET_r}^s$ is the error-based trust between node r and node s.

The energy consumption of each node is calculated based on the energy model presented in Equations (7) and (8) for the energy dissipated during transmission and reception, respectively.

$$\xi_{tr}(p,l) = \xi_{ele} * p + \xi_{amp} * p * l^2 \tag{7}$$

$$\xi_{rx}(p) = \xi_{ele} * p \tag{8}$$

where

ξ_{tr} is the energy dissipated during transmission;
ξ_{ele} specifies the energy consumed by the electronic components;
p indicates the number of bits in the transmitted packets;
ξ_{amp} shows the propagation constant;
l refers to the distance;
ξ_{rx} is the energy dissipated during the reception of data.

2.1.2. Simulations in Different Wireless Technologies

Aside from simulating the WSN in static and dynamic scenarios, we also conduct simulations by varying the wireless communication technology in each simulation scenario. This allows us to comprehensively assess the performance of different CH selection and routing optimization algorithms in various networking environments. Bluetooth, LoRa, Zigbee, and Wi-Fi were chosen as the wireless communication technologies in the simulation due to their varied data rate, energy consumption, and transmission range characteristics. Simulating under different wireless technologies allows us to gain insights into how each algorithm adapts to varying wireless conditions and the impact of each technology on key performance metrics.

LoRa technology was developed for low-power and long-range wireless communication, making it ideal for applications like smart agriculture, remote sensing, and urban Internet of Things (IoT) systems [27,28]. This technology utilizes the unlicensed radio spectrum in the ISM band, which are the 433 MHz, 868 MHz, and 915 MHz frequency bands. The data rate for this technology can reach up to 50 Kbps and reach up to a 10 km transmission range. Zigbee is another wireless communication technology designed by the Zigbee Alliance to support machine-to-machine (M2M) communications and other IoT networks that require low-cost, energy-efficient, and low-data-rate capabilities [28,29]. Typically, this technology is used for short-range communication with nodes within a 10–100 m transmission range. Zigbee also operates on unlicensed ISM frequency bands such as 868 MHz, 915 MHz, and the 2.4 GHz band. Zigbee supports data rates up to 250 Kbps.

Wi-Fi is known for its high data rates, supporting up to 54 Mbps for the 2.4 GHz band [30]. This technology is often used in applications requiring higher data throughput, such as video surveillance, large-scale monitoring, and intelligent building systems. However, its high data rate comes with higher energy consumption than other wireless technologies. Data transmission using this technology can reach a maximum of a few hundred meters. The Bluetooth low energy (BLE) is an improved version of the old Bluetooth technology with the special characteristics of low power, making it ideal for WSNs and IoT applications where power consumption is critical [31–33]. This wireless technology operates in the ISM band of 2.4 GHz. BLE supports transmission range from 10 m up to 100 m and data rates up to 1 Mbps. Table 2 summarizes the different parameters for each wireless technology that was used in this study.

Table 2. Summary of wireless technologies parameters.

Wireless Technology	**Parameters**			
	Range	**Energy Consumption**	**Data Rate**	**Frequency**
LoRa	Up to 10 km	Low	50 Kbps	433 MHz, 868 MHz, 915 MHz
Zigbee	10–100 m	Low	250 Kbps	868 MHz, 915 MHz, 2.4 GHz
Wi-Fi	Up to 100 m	Medium	0.1–54 Mbps	2.4 GHz
Bluetooth Low Energy (BLE)	Up to 100 m	Low	1 Mbps	2.4 GHz

2.2. Proposed Chronological Wild Geese Optimization (CWGO) Algorithm

During the WSN simulation, the optimal CH and routing path for data transmission is selected using the chronological wild geese optimization algorithm, which integrates the chronological concept within the wild geese optimization algorithm (WGA). WGA is a bio-inspired algorithm based on the swarm behavior of wild geese in nature, drawing on traits such as group migration, evolution, and natural attrition. This algorithm is designed to handle complex, high-dimensional optimization tasks efficiently with low computational demands, making it straightforward to implement. In the WGA, individuals adjust their positions based on interactions with neighboring members. The algorithm operates through several stages: group migration, foraging, reproduction and evolution, death, migration, and structured evolution. Although WGA has these advantages, it has not been widely applied to solve large, real-time complex problems. By integrating a chronological concept, the convergence rate of WGA is further improved, as this concept enables updating solutions over various time intervals. After selecting CH, the next step is to identify the optimal route for data transmission to enhance energy efficiency and communication reliability. The CWGO method is employed to determine the best path from several available routes, evaluating factors such as delay, distance, estimated energy, and trust value. The pseudocode of the proposed CWGO algorithm is presented in Algorithm 1.

Algorithm 1. Pseudocode of CWGO
Input: Initialize population y_1, $R_k^{e=1} = [0]$
Begin
Measure fitness with $Fit_1 = \frac{1}{5}\left[\delta_1 + (1-\delta_2) + (\zeta_p) + (1-\vartheta) + (LLT)\right]$, and $N = y_1$
Identify personal best H_k and global best K for all geese
While $N \leq N_{max}$
Sort the members from best to worst
For $k = 1 : y$
Pick the organized wild geese $e-1,\ e+1$, and $e+2$
For $z = 1 : W$
Estimate R_k^e with $R_{k,z}^{e+1} = (f_{1,z}R_{k,z}^e + f_{2,z}(R_{k+1,z}^e - R_{k-1,z}^e)) + f_{3,z}(H_{k,z}^e - Y_{k-1,z}^e) + f_{4,z}(H_{k+1,z}^e - Y_{k,z}^e) + f_{5,z}(H_{k+1,z}^e - Y_{k+1,z}^e) - f_{6,z}(H_{k-1,z}^e - Y_{k+2,z}^e)$
End for
For $z = 1 : W$
Determine $Y_{k,z}^m$ with $Y_{k,z}^m = H_{k,z}^e + f_{7,z}f_{8,z}((N_z^e + H_{k+1,z}^e - 2H_{k,z}^e) + R_{k,z}^{e+1})$
End for
For $z = 1 : W$
Determine $Y_{k,z}^{ws}$ with $Y_{k,z}^{ws} = H_{k,z}^e + f_{9,z}f_{10,z}(H_{k+1,z}^e - H_{k,z}^e)$
End for
For $z = 1 : W$
Determine $Y_{k,z}^{e+1}$ with $Y_{k,z}^{e+1} = Y_{k,z}^m$ or $Y_{k,z}^{e+1} = \frac{1}{2}\left[2H_{k,z}^e + f_{9,z}f_{10,z}(2H_{k+1,z}^e - 2H_{k,z}^e - H_{k+1,z}^{e-1} + H_{k,z}^{e-1}) - H_{k,z}^{e-1} + Y_{k,z}^e\right]$
End for
Check feasibility
End for
$N = N + y$
Estimate y with $y = round(y_1 - (y_1 - y_2)\left(\frac{N}{N_{max}}\right))$
End while
end

2.3. Proposed Unified Performance Metric

This paper proposes a simplified yet comprehensive approach to evaluating various WSN routing and cluster head (CH) selection algorithms. Traditionally, routing and CH selection studies utilize multiple individual metrics to assess algorithm performance. However, this multi-metric approach often leads to confusion, as different WSN applications prioritize different performance criteria. By consolidating critical metrics into a unified performance measure, we streamline the evaluation process and provide a more straightforward, adaptable framework for comparing algorithms across diverse applications and WSN scenarios.

2.3.1. Components of the Unified Performance Metric

The unified performance metric is developed using the four primary evaluation metrics used in our previous paper [13] as follows:

(i) Delay (ϑ): This metric shows the end-to-end delay experienced during data transmission from the sensor node to the base station through multi-hop CH routing. The delay affects data transmission speed, which is crucial in time-sensitive applications or applications requiring low latency. The delay is calculated using Equation (3).

(ii) Distance (D): The total distance data packets travel from a sensor node until they reach the sink node or the BS are also calculated by utilizing Equations (1) and (2) for the intra-cluster and inter-cluster distance. A lower distance typically represents a more efficient routing, thus reducing energy consumption and transmission time.

(iii) Residual Energy (ξ_r): The residual energy of each node is also calculated after each simulation round using Equation (9) below, where ξ_o indicates the initial energy, and ξ_{cons} denotes the consumed energy found with Equation (7) or Equation (8). Energy efficiency is very critical in any WSN application since it directly impacts network lifespan.

$$\xi_r = \xi_o - \xi_{cons} \tag{9}$$

(iv) Trust (T): The trust for each node, which represents how reliable a particular node is and also represents the integrity of data transmission using that specific node, is calculated using Equation (10), where DT, IT, and ET are calculated using Equations (4)–(6) from the previous section. Higher trust values correlate with more reliable data transmission, reducing the need for retransmissions and improving network efficiency. This is important for WSN applications where the networks are prone to node failure or interference.

$$T = \frac{1}{3}(DT + IT + ET) \tag{10}$$

2.3.2. Formulation of the Unified Performance Metric

The development of a unified metric for WSN performance begins with normalizing the component metrics discussed in Section 2.3.1 using the standard normalization formula given in Equation (11). Normalizing provides each component with a metric standard scale and ensures that each parameter contributes proportionally to the unified metric without being skewed to its original scale.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{11}$$

This is followed by creating a fitness function using the four components metric in Section 2.3.1: delay, distance, residual energy, and trust. We use Equation (12) as the fitness function that defines the overall performance of the WSN for the different CH and routing path selection algorithms.

$$Fit = \lambda_1 \xi_{rnorm} + \lambda_2 D_{norm} + \lambda_3 \vartheta_{norm} + \lambda_4 T_{norm} \tag{12}$$

where

ξ_{rnorm} is the normalized residual energy;
D_{norm} is the normalized distance;
ϑ_{norm} is the normalized delay;
T_{norm} is the normalized trust value;
λ_1, λ_2, λ_3, λ_4 are constant coefficients having values of 0.25, -0.25, -0.25, and 0.25, respectively.

2.3.3. Integration of Lagrange Interpolation

Lagrange interpolation has been widely used in the literature for various purposes, such as in network security and efficient data transmission in WSN [34–37], optimizing resource distribution [38,39], and error detection and correction in WSN [40]. In this paper, we proposed using Lagrange interpolation to create a function that can evaluate the performance of a WSN at different rounds using the fitness function discussed in Equation (12). Lagrange interpolation allows us to represent the relationship between the network's overall performance and the number of rounds in the simulation. Given Fit_j as the overall performance of the WSN at round j, we can express the Lagrange-interpolating polynomial $P(x)$ in Equation (13).

$$P(x) = \sum_{j=0}^{n} (Fit_j \prod_{i=0,\ i\neq j}^{n} \frac{x - x_i}{x_j - x_i}) \tag{13}$$

where

n represents the number of data points or the number of rounds;
x is the independent variable representing the number of round;
$x_i,\ x_j$ are the known data points that represent the number of round.

The integration of Lagrange interpolation, which combines different metrics into a unified metric, allows us to evaluate WSN's performance over time or as the number of rounds progresses. This allows us to comprehensively measure the network's behavior throughout the simulation and predict its performance for unknown data points.

3. Results

This Section presents the findings from the simulation of WSN with both static and dynamic sensor nodes at various WSN configurations. The simulation of the different WSN configurations was carried out on a PC using Python language. A comparative evaluation of the different advanced CH and routing selection algorithms using the proposed unified metric was also presented in this Section. A sample illustration of the GUI of the application and the simulation result are presented in Figure 2.

(**a**) (**b**)

Figure 2. (**a**) Graphical user interface of the simulator; (**b**) sample simulation result with 150 sensor nodes at 1000 rounds.

3.1. Simulation Results for Static Nodes

This subsection presents the simulation results for WSN with static sensor nodes. The static WSN is simulated for 100 and 1000 sensor nodes and for different wireless technologies, namely LoRa, WiFi, Zigbee, and Bluetooth. The simulations were conducted for 500, 1000, 1500, and 2000 rounds. Figure 3a–d display the plot for the Lagrange polynomial that represents the performance of different CH and routing selection algorithms based on the unified evaluation metric presented in Sections 2.3.2 and 2.3.3 for 100 sensor nodes using LoRa technology, Wi-Fi, Zigbee, and Bluetooth low energy, respectively. Figure 4a–d also illustrate the Lagrange polynomial plot for 1000 nodes using LoRa, Wi-Fi, Zigbee, and Bluetooth low energy, respectively. The plots for each result are obtained using Python language and the necessary libraries for constructing the Lagrange-interpolating polynomial, such as SciPy, numpy, pandas, and matplotlib.

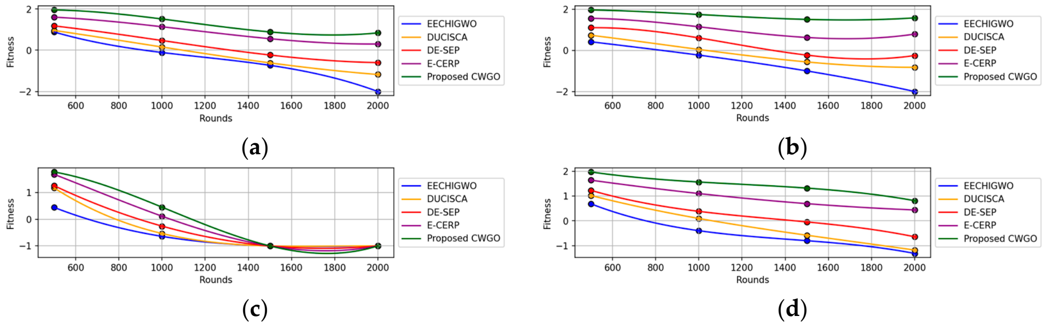

Figure 3. Lagrange polynomial plot of each algorithm at 100 sensor nodes: (**a**) plot using LoRa technology; (**b**) plot using Wi-Fi technology; (**c**) plot using Zigbee technology; (**d**) plot using Bluetooth low energy technology.

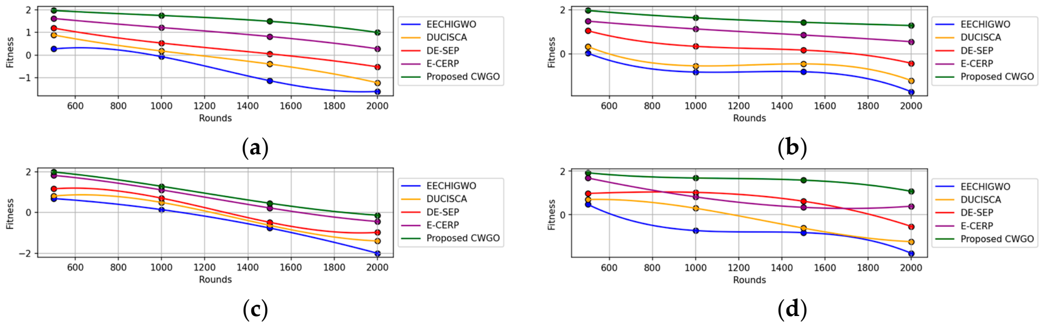

Figure 4. Lagrange Polynomial plot of each algorithm at 1000 sensor nodes: (**a**) plot using LoRa technology; (**b**) plot using Wi-Fi technology; (**c**) plot using Zigbee technology; (**d**) plot using Bluetooth low energy technology.

3.2. Simulation Results for Dynamic Nodes

This Subsection presents the simulation results for dynamic nodes, in which the sensor nodes change their position every after a round. The WSN is simulated in multiple configurations by varying its number of nodes from 100 to 1000, the number of rounds from 500, 1000, 1500, and 2000, and the type of wireless communication technology used, which are LoRa, Wi-Fi, Zigbee, and Bluetooth low energy. Figure 5a–d illustrate the performance of the different CH and routing selection algorithms across rounds using the proposed unified evaluation metric and with different wireless technologies for 1000 sensor nodes. Figure 6a–d also illustrate the performance of the algorithms across rounds for 1000 sensor nodes using a Lagrange polynomial plot. It can be observed that the proposed CWGO has the highest fitness value throughout the simulation rounds for LoRa, Wi-Fi, Zigbee, and Bluetooth low energy.

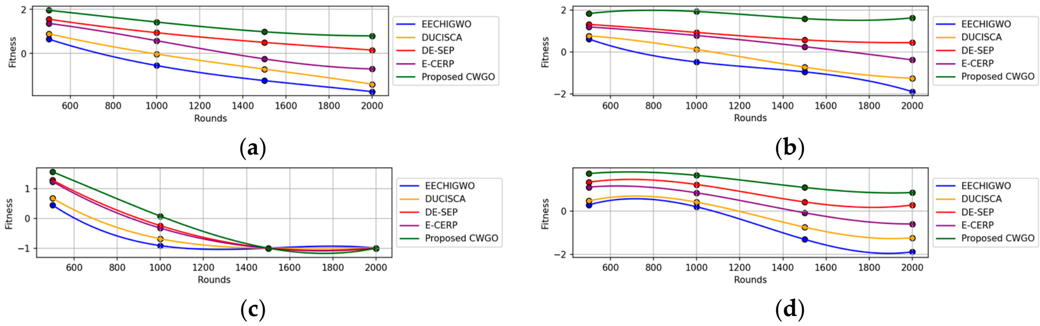

Figure 5. Lagrange polynomial plot of each algorithm at 100 dynamic sensor nodes: (**a**) plot using LoRa technology; (**b**) plot using Wi-Fi technology; (**c**) plot using Zigbee technology; (**d**) plot using Bluetooth low energy technology.

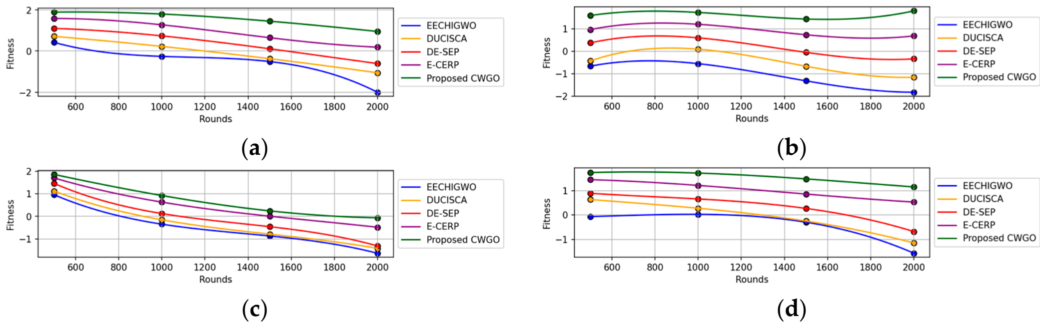

Figure 6. Lagrange polynomial plot of each algorithm at 1000 dynamic sensor nodes: (**a**) plot using LoRa technology; (**b**) plot using Wi-Fi technology; (**c**) plot using Zigbee technology; (**d**) plot using Bluetooth low energy technology.

3.3. Performance Evaluation with Increasing Number of Nodes

This paper also investigates the performance of each CH and routing selection algorithm with an increasing number of sensor nodes ranging from 100 to 1000 nodes for both static and dynamic scenarios. The researchers use the same fitness function presented in Equation (12) as the unified performance metric that integrates the four components metrics, namely delay, distance, trust, and energy. A Lagrange interpolation polynomial is then developed using Equation (13), which relates the number of sensor nodes to the overall performance of each algorithm. The type of wireless communication technology also varied to illustrate how well the different algorithms performed using different wireless communication technologies. Tables 3–10 tabulate the unified metric that was calculated using the Lagrange interpolation polynomial across different wireless technologies and different algorithms for both static and dynamic sensor node setups. It can be observed that the proposed CWGO algorithm consistently obtained the highest unified metric against other algorithms for each WSN configuration. For instance, in the static nodes setup, the highest fitness value was obtained: 1.857010 for LoRa, 1.918319 for Wi-Fi, 1.39495 for Zigbee, and 1.841392 for BLE. While for the dynamic node setup, the proposed CWGO still showed its superiority against the other four algorithms, as it obtained the highest fitness value of 1.88861 for LoRa, 1.962191 for Wi-Fi, 1.305493 for Zigbee, and 1.8676 for BLE.

Table 3. Unified fitness table for LoRa with static nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	0.868638	0.934589	1.087994	1.388729	1.668023
200	0.882495	1.051989	1.231873	1.516992	1.660873
300	0.735453	0.999764	1.198011	1.496727	1.659858
400	0.264741	0.794149	1.228907	1.456350	1.663382
500	0.869429	1.163625	1.388859	1.637992	1.805647
600	1.011312	1.120711	1.268510	1.639834	1.818944
700	1.046406	1.244517	1.394943	1.615182	1.821575
800	1.137700	1.243303	1.410109	1.621443	1.768320
900	0.547656	1.210099	1.367186	1.576743	1.816044
1000	0.777984	1.279889	1.452959	1.650118	1.857010

Table 4. Unified fitness table for Wi-Fi with static nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	1.058142	1.187094	1.37696	1.663009	1.918319
200	0.961377	1.06743	1.456871	1.737297	1.915923
300	1.019475	1.246388	1.439662	1.692321	1.894772
400	1.094013	1.171898	1.323396	1.709505	1.855184
500	0.950436	1.260213	1.42596	1.682926	1.828962
600	0.693115	0.888402	1.28584	1.68924	1.867463
700	0.625663	0.881736	1.353209	1.673023	1.841342
800	1.100234	1.175227	1.436513	1.702083	1.867656
900	0.539643	1.122186	1.432111	1.631167	1.820818
1000	0.974614	1.11313	1.507938	1.694352	1.87379

Table 5. Unified fitness table for Zigbee with static nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	−1.439674	−1.017681	−0.9423	−0.393427	−0.275144
200	−0.350244	−0.143026	0.02457	0.35009	0.477618
300	0.128404	0.224365	0.370293	0.70703	0.828585
400	−0.271594	0.179051	0.334494	0.676933	0.818316
500	0.161342	0.418342	0.716239	0.990951	1.115441
600	0.194407	0.52966	0.686343	0.981651	1.085753
700	0.342435	0.50558	0.719503	1.020723	1.174982
800	0.504004	0.594011	0.75023	1.153093	1.278081
900	0.319147	0.505741	0.821704	1.097995	1.326107
1000	0.312404	0.426058	0.713354	1.244586	1.39495

Table 6. Unified fitness table for BLE with static nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	0.621096	0.79834	0.977211	1.303532	1.576598
200	0.904261	1.010625	1.273248	1.54376	1.752376
300	0.619386	1.1014	1.350222	1.575911	1.841392
400	0.775809	1.062028	1.26269	1.483018	1.610179
500	1.050969	1.122053	1.310433	1.582832	1.720262
600	0.885958	1.023522	1.134627	1.468225	1.701378
700	0.676728	0.768763	1.338767	1.650267	1.785547
800	0.483629	0.847986	1.098362	1.622983	1.820718
900	0.932442	1.112305	1.279319	1.529749	1.803926
1000	0.985515	1.126923	1.268089	1.672561	1.803429

Table 7. Unified fitness table for LoRa with dynamic nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	0.891403	0.970041	1.506215	1.188897	1.721931
200	0.89945	1.055368	1.202339	1.545608	1.749904
300	0.950528	1.04382	1.272961	1.53997	1.747165
400	1.112222	1.254274	1.411318	1.713736	1.839128
500	1.095187	1.20064	1.333248	1.581796	1.804019
600	1.000979	1.224901	1.424861	1.637332	1.816057
700	1.136022	1.205493	1.418211	1.700539	1.82851
800	0.846979	1.042231	1.205244	1.502281	1.764686
900	0.842953	0.956747	1.412229	1.622343	1.88861
1000	0.925562	1.125699	1.344521	1.619013	1.812704

Table 8. Unified fitness table for Wi-Fi with dynamic nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	1.116731	1.217488	1.590118	1.426334	1.890354
200	1.119663	1.241554	1.417521	1.657396	1.909969
300	1.231319	1.319504	1.455968	1.693119	1.889339
400	1.193607	1.27684	1.569381	1.806398	1.958035
500	1.15476	1.301576	1.474626	1.733888	1.923132
600	0.995174	1.245588	1.416756	1.705448	1.905322
700	1.00918	1.090077	1.36754	1.63823	1.927473
800	1.144372	1.306148	1.461129	1.668384	1.962191
900	0.970547	1.16201	1.278771	1.649537	1.811819
1000	1.050889	1.133248	1.436473	1.665954	1.847831

Table 9. Unified fitness table for Zigbee with dynamic nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	−1.088405	−1.014428	−0.525501	−0.595907	−0.242875
200	−0.245831	−0.107404	0.117948	0.468571	0.551786
300	0.129421	0.279013	0.394649	0.735413	0.882393
400	−0.137825	0.172671	0.356507	0.688107	0.857051
500	−0.041443	0.245884	0.483252	0.810451	0.930534
600	0.421275	0.516029	0.634349	0.897887	1.12969
700	0.491213	0.623307	0.760308	1.050573	1.140344
800	0.114004	0.445772	0.720768	0.948353	1.10077
900	0.55125	0.749592	0.879718	1.120389	1.246854
1000	0.71005	0.824898	0.996566	1.19612	1.305493

Table 10. Unified fitness table for BLE with dynamic nodes.

Number of Sensor Nodes	EECHIGWO	DUCISCA	DE-SEP	E-CERP	Proposed CWGO
100	0.787118	0.912644	1.34219	1.120444	1.629341
200	0.787118	0.912644	1.34219	1.120444	1.629341
300	1.129613	1.247557	1.394609	1.638651	1.779021
400	1.008761	1.162567	1.384479	1.635785	1.838343
500	1.017553	1.287576	1.523731	1.726402	1.8676
600	0.861086	1.330822	1.476195	1.675812	1.827526
700	1.065576	1.225694	1.326939	1.712353	1.845613
800	1.009266	1.201164	1.479747	1.717936	1.840102
900	0.991727	1.164263	1.361375	1.617569	1.789958
1000	0.420093	1.013169	1.17755	1.497468	1.67134

3.4. Algorithms Execution Time

The execution time for each algorithm was evaluated to assess their computational efficiency in selecting cluster heads (CHs) and determining routing paths for data transmission. Execution time is a critical factor for algorithms used in wireless sensor networks (WSNs), as real-time or near-real-time performance is often required for many applications, especially in dynamic environments or resource-constrained settings. The running time presented in Table 11 was calculated by recording the start and end time of the CH selection and routing-path determination processes for each algorithm. It can be observed that for 50 sensor nodes with 500 rounds of simulation, the proposed CWGO algorithm demonstrated the fastest execution time at 13.548 s, highlighting its efficiency in real-time applications. E-CERP followed with 16.215 s, attributed to its simpler optimization process. DE-SEP and DUCISCA showed moderate execution times of 18.554 and 20.632 s, respectively, balancing performance and computational demands. EECHIGWO had the longest execution time at 25.986 s, reflecting the additional overhead from its iterative optimization and breeding processes.

Table 11. Running time for each algorithm.

Algorithm	Running Time (Seconds)
EECHIGWO	25.986
DUCISCA	20.632
DE-SEP	18.554
E-CERP	16.215
Proposed CWGO	13.548

4. Discussion

The results presented in Section 3 allow us to visualize the performance of the proposed CWGO, DE-SEP, E-CERP, DUCISCA, and EECHIGWO algorithms on the selection of CHs and routing-path optimization in various WSN configurations using a unified performance metric. The WSNs were simulated for multiple rounds and multiple numbers of nodes in both static and dynamic scenarios across four different wireless technologies, namely LoRa, Wi-Fi, Zigbee, and BLE.

During the static WSN simulation for LoRa technology, the proposed CWGO algorithm consistently outperforms other algorithms in 100- and 1000-sensor node scenarios. While all algorithms show a decline in fitness over time, the CWGO's decline in performance is the most gradual, indicating its consistency as time progresses. This performance is also evident for 1000 sensor nodes, indicating its robustness and scalability even for a larger number of sensor nodes. In contrast, the EECHIGWO algorithm shows the lowest fitness value across the simulation rounds for both 100 and 1000 sensor node configurations. The performance of each algorithm using Wi-Fi technology also demonstrates the proposed CWGO's superior performance against the other algorithms. For both 100 and 1000 sensor node configurations, CWGO starts with the highest fitness value and retains its lead across 2000 rounds. DUCISCA, EECHIGWO, and DE-SEP show a significant decrease in performance at the latter end of the simulation, while E-CERP still lags behind the proposed CWGO by a considerable amount of fitness value. The results for Zigbee technology demonstrate the proposed CWGO algorithm's performance for low-power, short-range communication environments. CWGO's fitness remains consistently higher than that of the other algorithms despite the similarities in performance trends. While DUCISCA, E-CERP, and DE-SEP perform moderately, they cannot match the performance of CWGO, which shows better long-term network sustainability. As seen across other technologies, EECHIGWO performs poorly, failing to maintain competitive fitness values due to its inefficiency in conserving energy in low-power Zigbee networks. In Bluetooth low energy (BLE) technology, the performance of all algorithms begins with closer fitness values, reflecting the challenges posed by BLE's low-power, energy-constrained environment. However, as the simulation progresses, the proposed CWGO algorithm gradually widens the performance gap against other algorithms.

The dynamic WSN results are identical to those of the static WSN simulation. For instance, in LoRa technology, for both 100 and 1000 sensor node setups, the proposed CWGO algorithm begins with the highest fitness value, maintaining its lead across all 2000 rounds. This shows the CWGO's flexibility in complex dynamic environments where sensor node movements and increasing network density are present. EECHIGWO again performed the worst, with its fitness value dropping sharply at the end of the simulation for 1000 nodes, while DUCISCA, DE-SEP, and E-CERP showed moderate performance. For Wi-Fi technology, the proposed CWGO continues to outperform other algorithms in both 100 and 1000 dynamic node configurations. The performance of each algorithm for Zigbee technology shows a sharper decline as the simulation round progresses. Similar to static nodes, a similar trend is observed across all algorithms, and the gap between them is lesser than in other wireless technologies. Lastly, for BLE technology, at 1000 sensor nodes, E-CERP and CWGO started with an almost identical fitness value, but their gap widens as the simulation round increases, in which CWGO performs better. This is also the case for DUCISCA and DE-SEP, where they started the simulation with an identical fitness value, but their performance gap widens, and a decline in their performance value is observed across rounds.

The performance of each algorithm with an increasing number of sensor nodes across different wireless technologies for both static and dynamic node setups demonstrates their scalability across various application areas. The result presented in Tables 3–10 shows that the proposed CWGO achieves the highest unified metric value across all node configurations for each wireless technology. This is particularly noteworthy in the LoRa and Wi-Fi setups, where CWGO's unified metric value increases with larger node counts, indicating its superiority in handling larger network sizes. The same trend is observed in the dynamic node setup, where CWGO continues to show its scalability and adaptability in changing network conditions. In contrast, EECHIGWO consistently underperforms across all wireless technologies, especially in larger-sensor-node configurations. For instance, in Zigbee and BLE setups, EECHIGWO shows a significant drop in performance, with its fitness reaching as low as -1.4397 for 100 nodes in Zigbee. Similarly, in the dynamic Zigbee setup, EECHIGWO starts poorly, with a fitness value of -1.0884 for 100 nodes, and only slightly improves to 0.7101 for 1000 nodes. DUCISCA and DE-SEP perform moderately across most technologies, but their fitness values fluctuate more as the number of sensor nodes increases, suggesting they may not be as reliable for larger or more complex WSN setups. This fluctuation can be observed in both static and dynamic setups. For example, in the dynamic Zigbee setup, DUCISCA starts with -1.0144 for 100 nodes but improves to 0.8249 for 1000 nodes. Although this shows better performance over time, it still lags behind CWGO's dynamic performance, which reaches 1.3055 for 1000 nodes in Zigbee. DE-SEP similarly shows moderate improvement but cannot surpass CWGO's consistent lead in dynamic environments. E-CERP demonstrates competitive performance across all node configurations, particularly in Wi-Fi and BLE setups; however, it still falls short of surpassing CWGO performance, especially in larger-node setups.

In addition to assessing the overall performance trends in the proposed CWGO algorithm, a deeper examination of the factors contributing to the performance degradation of the comparison algorithms—DE-SEP, E-CERP, DUCISCA, and EECHIGWO—highlights their respective strengths and limitations in various WSN configurations and environments. Specifically, the performance decline of EECHIGWO across all wireless technologies can be attributed to its limited energy conservation mechanisms, particularly in energy-constrained environments like Zigbee and BLE. This algorithm's lack of efficient energy management results in faster energy depletion, leading to a more rapid decrease in fitness value as the simulation rounds progress. Furthermore, both DUCISCA and DE-SEP demonstrate moderate but inconsistent performance, with noticeable fluctuations in fitness values as the number of sensor nodes increases. These fluctuations are more prominent in dynamic WSN setups, where node mobility and network density changes increase the complexity of maintaining optimal CH selection and routing paths. The observed fluctuations suggest that DUCISCA and DE-SEP may be less adaptable to environments with high variability, which could limit their applicability in highly dynamic WSN scenarios. For E-CERP, although it performs competitively in static setups with fewer nodes, its fitness value begins to lag behind CWGO in larger or more dynamic configurations. This may be due to E-CERP's limited scalability and reduced adaptability when dealing with larger networks and complex routing requirements. The degradation in performance over time suggests that while E-CERP is suitable for moderate-scale WSNs, it faces challenges in maintaining high efficiency in larger, resource-intensive setups.

The proposed CWGO algorithm demonstrates high efficiency in energy consumption, low latency, and robust performance in both static and dynamic WSN environments, as well as across different wireless communication technologies. This flexibility enables its application in diverse communication networks and scenarios, such as smart city infrastructures and large industrial sensor networks where scalability and robustness are crucial.

However, one of the disadvantages of CWGO is its computational complexity, which can become an issue in larger networks, especially in resource-constrained environments where computational resources are limited.

The proposed unified metric's main advantage lies in its balanced and straightforward approach, offering a comprehensive view of WSN performance by combining multiple critical metrics. This unified evaluation approach is beneficial in assessing overall network efficiency, particularly for large-scale comparisons. However, there may be application-specific scenarios where the weight of each component metric within the unified evaluation would need to be adjusted to reflect specific priorities or performance requirements.

5. Conclusions

This paper presents a comprehensive evaluation of different CH selection and routing optimization methods, particularly the Chronological Wild Geese Optimization (CWGO) algorithm, in wireless sensor networks using a novel unified performance metric that integrates key factors such as energy, delay, distance, and trust. The unified metric was developed using Lagrange interpolation, which provides a more straightforward approach to evaluating the performance of CWGO and other algorithms across static and dynamic sensor node configurations in various wireless communication technologies, including LoRa, Wi-Fi, Zigbee, and BLE. The unified metric plays an important role since it offers a more comprehensive and balanced assessment of WSN performance, as traditional approaches often focus on individual metrics that fail to capture the network's overall efficiency. The results demonstrate that CWGO consistently achieves the highest unified metric scores across all node configurations and technologies, indicating its superior ability to balance energy efficiency, transmission delay, trust, and data-routing distance. The use of the unified metric reveals CWGO's robustness, not only in small-scale networks but also in large, complex WSN scenarios, particularly in dynamic node setups where environmental changes and mobility are prevalent. The superior performance of CWGO, as revealed by the unified metric, positions it as a highly effective algorithm for optimizing WSNs, particularly in scenarios requiring scalability, energy efficiency, and adaptability to dynamic environments. Despite CWGO's advantages, certain limitations should be acknowledged. One potential drawback is the algorithm's computational complexity, which could impact its performance in resource-constrained environments where processing power and memory are limited. This constraint may lead to reduced efficiency when deploying CWGO in large-scale WSNs, especially in real-time applications. Additionally, while CWGO adapts well in moderately dynamic environments, its performance in highly unpredictable or extreme conditions—such as highly mobile or rapidly changing network topologies—has not been thoroughly explored. Future research could optimize CWGO's computational demands to enhance its applicability in low-resource settings and extend its adaptability to more challenging environments. Introducing adaptive weight adjustments during the optimization process could also provide better flexibility and further enhance the algorithm's performance under varied scenarios. Additionally, validating CWGO's performance in diverse real-world environments would provide practical insights and ensure the algorithm's robustness in a wide range of WSN applications. Exploring hybrid approaches that integrate CWGO with other optimization techniques, such as machine learning or evolutionary algorithms, could offer further improvements in performance, particularly for scenarios with unique constraints or specific application requirements. These hybrid solutions may enhance CWGO's adaptability, scalability, and overall effectiveness in diverse WSN applications.

Lastly, future research should expand the range of simulated scenarios to include more varied and extreme network conditions, such as highly mobile sensor nodes and rapidly evolving topologies. Such efforts would allow a more comprehensive understanding of CWGO's strengths and limitations, enabling it to address the unique challenges posed by different application areas. The feasibility of implementing the proposed CWGO in real-world environments, such as smart city infrastructure or industrial IoT systems, also remains an exciting direction for future study.

This unified approach to performance evaluation is crucial for future research in WSNs, as it offers a better understanding of algorithmic behavior across diverse applications and network conditions. The findings of this study hold significant practical implications for wireless communication applications. CWGO's energy efficiency makes it suitable for battery-powered devices where minimizing energy consumption during wireless data transmission is critical to prolonging the network lifespan, such as in environmental monitoring and industrial sensor networks. Additionally, its scalability and robustness in handling large networks make it ideal for smart city applications, where numerous sensors need efficient, reliable communication across wide areas.

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References

1. Palan, N.G.; Barbadekar, B.V.; Patil, S. Low Energy Adaptive Clustering Hierarchy (LEACH) Protocol: A Retrospective Analysis. In Proceedings of the International Conference on Inventive Systems and Control (ICISC 2017), Coimbatore, India, 19–20 January 2017; pp. 1–12. [CrossRef]
2. Vinitha, A.; Rukmini, M.S.S.; Dhirajsunehra. Secure and Energy Aware Multi-Hop Routing Protocol in WSN Using Taylor-Based Hybrid Optimization Algorithm. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 1857–1868. [CrossRef]
3. Chatterjee, S.; Singh, M. A Centralized Energy-Efficient Routing Protocol for Wireless Sensor Networks. *Int. J. Adv. Netw. Appl.* **2012**, *3*, 12–18.
4. Jha, S.K.; Eyong, E.M. An Energy Optimization in Wireless Sensor Networks by Using Genetic Algorithm. *Telecommun. Syst.* **2018**, *67*, 113–121. [CrossRef]
5. Majeed, D.M.; Rabee, H.W.; Ma, Z. Improving Energy Consumption Using Fuzzy-GA Clustering and ACO Routing in WSN. In Proceedings of the 2020 3rd International Conference on Artificial Intelligence and Big Data (ICAIBD 2020), Chengdu, China, 28–31 May 2020; pp. 293–298. [CrossRef]
6. Sharmin, S.; Ahmedy, I.; Noor, R.M. An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO. *Energies* **2023**, *16*, 2487. [CrossRef]
7. Karasekreter, N.; Şahman, M.A.; Başçiftçi, F.; Fidan, U. PSO-Based Clustering for the Optimization of Energy Consumption in Wireless Sensor Network. *Emerg. Mater. Res.* **2020**, *9*, 776–783. [CrossRef]
8. Moussa, N.; El Belrhiti El Alaoui, A. An Energy-Efficient Cluster-Based Routing Protocol Using Unequal Clustering and Improved ACO Techniques for WSNs. *Peer-to-Peer Netw. Appl.* **2021**, *14*, 1334–1347. [CrossRef]
9. Zivkovic, M.; Bacanin, N.; Zivkovic, T.; Strumberger, I.; Tuba, E.; Tuba, M. Enhanced Grey Wolf Algorithm for Energy Efficient Wireless Sensor Networks. In Proceedings of the 2020 Zooming Innovation in Consumer Technologies Conference (ZINC 2020), Novi Sad, Serbia, 26–27 May 2020; pp. 87–92. [CrossRef]
10. Jaiswal, K.; Anand, V. A Grey-Wolf Based Optimized Clustering Approach to Improve QoS in Wireless Sensor Networks for IoT Applications. *Peer-to-Peer Netw. Appl.* **2021**, *14*, 1943–1962. [CrossRef]
11. Pakdel, H.; Fotohi, R. A Firefly Algorithm for Power Management in Wireless Sensor Networks (WSNs). *J. Supercomput.* **2021**, *77*, 9411–9432. [CrossRef]
12. Alghamdi, T.A. Energy Efficient Protocol in Wireless Sensor Network: Optimized Cluster Head Selection Model. *Telecommun. Syst.* **2020**, *74*, 331–345. [CrossRef]
13. Mabunga, Z.P.; Dela Cruz, J.C. Chronological Wild Geese Optimization Algorithm for Cluster Head Selection and Routing in Wireless Sensor Network. *Int. J. Commun. Syst.* **2024**, *1*, e5963. [CrossRef]

14. Reddy, M.R.; Chandra, M.L.R.; Venkatramana, P.; Dilli, R. Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm. *Computers* **2023**, *12*, 35. [CrossRef]
15. Zhu, F.; Wang, W. A Distributed Unequal Clustering Routing Protocol Based on the Improved Sine Cosine Algorithm for WSN. *J. Sens.* **2022**, *2022*, 7382098. [CrossRef]
16. Osamy, W.; Salim, A.; Khedr, A.M. An Information Entropy Based-Clustering Algorithm for Heterogeneous Wireless Sensor Networks. *Wirel. Netw.* **2020**, *26*, 1869–1886. [CrossRef]
17. Dattatraya, K.N.; Rao, K.R. Hybrid Based Cluster Head Selection for Maximizing Network Lifetime and Energy Efficiency in WSN. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 716–726. [CrossRef]
18. Mohamad, M.M.; Kheirabadi, M.T. Energy Efficient Opportunistic Routing Algorithm for Underwater Sensor Network: A Review. In Proceedings of the 2016 2nd International Conference on Science in Information Technology (ICSITech), Yogyakarta, Indonesia, 26–27 October 2017; pp. 41–46. [CrossRef]
19. Hossan, A.; Choudhury, P.K. DE-SEP: Distance and Energy Aware Stable Election Routing Protocol for Heterogeneous Wireless Sensor Network. *IEEE Access* **2022**, *10*, 55726–55738. [CrossRef]
20. Xue, X.; Shanmugam, R.; Palanisamy, S.K.; Khalaf, O.I.; Selvaraj, D.; Abdulsahib, G.M. A Hybrid Cross Layer with Harris-Hawk-Optimization-Based Efficient Routing for Wireless Sensor Networks. *Symmetry* **2023**, *15*, 438. [CrossRef]
21. Cherappa, V.; Thangarajan, T.; Sundaram, S.S.M.; Hajjej, F.; Munusamy, A.K.; Shanmugam, R. Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks. *Sensors* **2023**, *23*, 2788. [CrossRef]
22. Vellaichamy, J.; Basheer, S.; Bai, P.S.; Khan, M.; Kumar Mathivanan, S.; Jayagopal, P.; Babu, J.C. Wireless Sensor Networks Based on Multi-Criteria Clustering and Optimal Bio-Inspired Algorithm for Energy-Efficient Routing. *Appl. Sci.* **2023**, *13*, 2801. [CrossRef]
23. Wu, M.; Li, Z.; Chen, J.; Min, Q.; Lu, T. A Dual Cluster-Head Energy-Efficient Routing Algorithm Based on Canopy Optimization and K-Means for WSN. *Sensors* **2022**, *22*, 9731. [CrossRef]
24. Wang, X.; Wu, H.; Miao, Y.; Zhu, H. A Hybrid Routing Protocol Based on Naïve Bayes and Improved Particle Swarm Optimization Algorithms. *Electronics* **2022**, *11*, 869. [CrossRef]
25. Al-Baz, A.; El-Sayed, A. A New Algorithm for Cluster Head Selection in LEACH Protocol for Wireless Sensor Networks. *Int. J. Commun. Syst.* **2018**, *31*, e3407. [CrossRef]
26. Singh, A.; Saini, H.S.; Kumar, N. D-MSEP: Distance Incorporated Modified Stable Election Protocol in Heterogeneous Wireless Sensor Network. In *Advances in Intelligent Systems and Computing*; Springer: Singapore, 2019; Volume 46, pp. 157–168.
27. Lavric, A.P.V. Internet of Things and LoRaTM Low-Power Wide-Area Networks: A Survey. In Proceedings of the 2017 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, 13–14 July 2017.
28. Ali, A.I.; Partal, S.Z.; Kepke, S.; Partal, H.P. ZigBee and LoRa Based Wireless Sensors for Smart Environment and IoT Applications. In Proceedings of the 2019 IEEE 1st Global Power, Energy and Communications Conference (GPECOM), Cappadocia, Turkey, 12–15 June 2019; pp. 19–23. [CrossRef]
29. Proskochylo, A.; Vorobyov, A.; Zriakhov, M.; Kravchuk, A.; Akulynichev, A.; Lukin, V. Overview of Wireless Technologies for Organizing Sensor Networks. In Proceedings of the 2015 2nd International Scientific Conference on Problems of Infocommunications Science and Technology (PIC S&T), Kharkiv, Ukraine, 13–15 October 2015; pp. 39–41. [CrossRef]
30. Kaushik, N.; Bagga, T.; Aggarwal, R.K. Comparative Study on IoT Technologies—Short & Long Range. *Int. J. Eng. Trends Technol.* **2020**, *68*, 37–42. [CrossRef]
31. Gomez, C.; Oller, J.; Paradells, J. Overview and Evaluation of Bluetooth Low Energy: An Emerging Low-Power Wireless Technology. *Sensors* **2012**, *12*, 11734–11753. [CrossRef]
32. Hortelano, D.; Olivares, T.; Ruiz, M.C.; Garrido-Hidalgo, C.; López, V. From Sensor Networks to Internet of Things: Bluetooth Low Energy, a Standard for This Evolution. *Sensors* **2017**, *17*, 372. [CrossRef]
33. Tosi, J.; Taffoni, F.; Santacatterina, M.; Sannino, R.; Formica, D. Performance Evaluation of Bluetooth Low Energy: A Systematic Review. *Sensors* **2017**, *17*, 2898. [CrossRef]
34. Hsiao, T.C.; Wu, Z.Y.; Chen, T.L.; Chung, Y.F.; Chen, T.S. A Hierarchical Access Control Scheme Based on Lagrange Interpolation for Mobile Agents. *Int. J. Distrib. Sens. Netw.* **2018**, *14*, 7890892. [CrossRef]
35. Monga, C.; Gupta, D.; Prasad, D.; Juneja, S.; Muhammad, G.; Ali, Z. Sustainable Network by Enhancing Attribute-Based Selection Mechanism Using Lagrange Interpolation. *Sustainability* **2022**, *14*, 6082. [CrossRef]
36. Lin, H.Y.; Pan, D.J.; Zhao, X.X.; Qiu, Z.R. A Rapid and Efficient Pre-Deployment Key Scheme for Secure Data Transmissions in Sensor Networks Using Lagrange Interpolation Polynomial. In Proceedings of the 2nd International Conference on Information Security and Assurance (ISA), Busan, Republic of Korea, 24–26 April 2008; pp. 261–265. [CrossRef]
37. Wan, C.; Zhang, J. Identity-Based Key Management for Wireless Sensor Networks Using Lagrange Interpolation. *Secur. Commun. Netw.* **2016**, *9*, 3713–3723. [CrossRef]
38. Harb, H.; Jaoude, C.A.; Makhoul, A. An Energy-Efficient Data Prediction and Processing Approach for the Internet of Things and Sensing-Based Applications. *Peer-to-Peer Netw. Appl.* **2020**, *13*, 780–795. [CrossRef]

39. Warpe, S.T.; Pippal, R.K.S. A Lagrange Interpolation Application for Automating Fertilizer Distribution in Agriculture Using Wireless Sensor Networks. *Agric. Sci. Dig.* **2024**, *44*, 618–624. [CrossRef]
40. Merhej, A.; Engineering, I. Lagrange Interpolating for Error Detection and Correction in Antijamming Attack. *J. Intell. Robot. Syst.* **2015**, *3*, 409–414.