Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Gaussian Distributive Clustering Based Multi-Objective Truncated Grasshopper Optimal Path Selection for Energy Efficient Routing in WSN

D. Mohanapriya [1], Dr. V. Saravanan [2]
[1] *Research Scholar & Assistant Professor, Department of Information Technology, Hindusthan College of Arts & Science College, Coimbatore, Tamil Nadu, India. Email: mohanapriyaphd31@gmail.com*
[2] *Professor & Head, Department of Information Technology, Hindusthan College of Arts & Science College, Coimbatore, Tamil Nadu, India. Email: vsreesaran@gmail.com*

ARTICLE INFO

Received: 28 Dec 2024

Revised: 10 Feb 2025

Accepted: 20 Feb 2025

ABSTRACT

WSN is network that contain numerous SN deployed within a specific region for sensing and collecting data as well as transmitting to the BS. WSNs consistently face challenges in delivering the information to the base station with minimal delay, energy utilization, and packet loss. Energy efficiency is also considered one of the major issues in the WSNs through the routing process. An efficient routing protocol is required to mention these constraints as well as enhance effectiveness of WSNs. Motivated by these challenges, a Gaussian Distributive Clustering-based Multi-Objective Truncated Grasshopper Optimization (GDC-MTGO) method is developed for effective data packet routing in WSN through high packet delivery ratio as well as minimal delay. GDC-MTGO method includes sensor node clustering, optimal route path identification, route maintenance. At first, number of SN is taken as input. Afterward, all SN in WSN are clustered depend on their energy level using the energy-aware Gaussian distributive Jenks Natural Break Node clustering technique. For every cluster, SN through superior residual energy considered as CH. Secondly, optimal route paths between cluster heads are identified with multi-objective truncated grasshopper optimization for broadcasting data packets to BS for further processing. In optimization process, the population of available route paths between source and sink node are initialized. Fitness of every route path is calculated depend on multi-objective functions. Truncated selection process is used to choose global best optimal path for resource-aware data broadcast. Finally, route maintenance is carried out by identifying substitute optimal route path when link malfunction happens. Experimental evaluation is carried out with different performance metrics with number of SN and number of data packets. Quantitatively analyzed outcomes denote GDC-MTGO method achieving higher data delivery, throughput and minimal energy consumption, delay, loss rate compared to existing methods.

Keywords: WSN, Energy Aware Routing, Gaussian distributive Jenks Natural Break Node Clustering Process, multi-objective functions, Meta-heuristic Grasshopper Optimization, truncated selection.

INTRODUCTION

WSNs consist of numerous sensor nodes that focus on data collection, processing, and transferring information as of source to BS in large-scale network. The main challenge in WSNs is managing scalability due to the distribution of huge number of SN through restricted energy resources. Efficient energy utilization plays a vital role in WSNs to expand network life span. Reducing energy consumption is crucial at WSN, and this process achieved through various methods. A significant approach employed to address this issue is clustering, which groups distributed nodes. The main focus is on developing efficient routing methods to enhance life span of WSNs.

A combination of two SFO-SHO hybrid frameworks was developed in [1] to enhance the energy-efficient routing based on efficient clustering optimal cluster head selection. But it did not focus on the link stability to minimize the

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

packet loss rate. Hybrid energy-aware routing technique, an integration of PSO as well as fuzzy clustering called (ECPF), was developed in [2] with the aim of improving throughput. But it was not considered to further extend the network lifetime.

An integration of quantum PSO and fuzzy system was developed in [3] for improving energy effectiveness and extending network life span. But it failed to guarantee a robust as well as consistent process at different and demandinG environments. A meta-inspired Hawks Fragment Optimization method was designed in [4] with the aim of selecting an optimum path and achieving better throughput. But the performance of end-to-end delay remained unaddressed. A chaotic genetic and grey wolf optimization algorithm were developed in [5] to reduce the entire energy utilization through choosing energy efficient CH. The designed algorithm also used for finding an optimal routing path. However result of throughput was not enhanced. An energy-efficient multi-hop routing protocol was designed [6] for expanding lifetime of network by applying hybrid optimization algorithms. But the designed protocol failed to implement the large-scale WSNs. But it failed to consider the integration of heterogeneous networks. An integration of fuzzy logic system and quantum annealing method was developed in [7] for routing the data packets to enhance stability of network as well as reduce the energy utilization. But it failed to consider the integration of heterogeneous networks.

Energy-efficient routing technique was developed [8] based on combinatorial random sampling bat optimization to preserve energy and extend the lifetime of network. However, it failed to guarantee data transmission and computational overhead measurements. An osprey optimization method was presented [9] based on energy-effective cluster head selection to improve the data delivery ratio. But, it failed to focus on finding link stability in WSN for better communication. An energy-aware cluster-basis of routing protocol was designed in [10] by applying a combination of snake optimizer as well as minimum spanning tree. But it failed to investigate stability of algorithm to provide better service quality in practical applications.

A federated deep reinforcement learning (FDRL) model was developed in [11] for routing the high-speed data packets within dynamic network conditions. But the model did not utilize the optimization techniques to enhance the routing performance with minimal delay. Improved centroid-based clustering protocol was presented [12] to provide energy-effective cluster head selection as well as to extend the network lifetime. But, achieving stability-aware routing posed a challenging issue. An intelligent energy-efficient data routing technique was developed [13] for WSNs to minimize energy consumption and prolong network lifespan. However designed method was not efficient in large-scale networks.

An enhanced ant colony algorithm was presented [14] to determine optimal route path for improving transmission quality with minimal delay. But it failed to develop more comprehensive and adaptable routing optimization methods to enhance network performance. Adaptive energy-effective clustering routing protocol was developed [15] that depend on the node density and the distances between the nodes. However, it failed to extend the lifetime of large-scale WSNs in the uneven node distribution.

1.1 Major contributions of the paper

- To enhance energy efficient routing in WSN, the GDC-MTGO method has been developed by applying a Gaussian distributive Jenks Natural Break Node clustering and multi-objective truncated grasshopper optimization method.
- To improve network life span as well as minimize the energy utilization, Gaussian distributive Jenks Natural Break The node clustering technique is employed for grouping the sensor nodes depend on their residual energy. The CH selection process enhances data delivery as well as reduces energy utilization.
- To enhance data delivery rates and minimize loss, the multi-objective truncated grasshopper optimization technique is utilized. This method aims to identify optimal route path, thereby improving data transmission and minimizing loss rates.
- To enhance throughput and minimize delay, the GDC-MTGO method employs the route maintenance process by selecting the other optimal path.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

- Finally, a complete simulation measurement was performed through various evaluation parameters to authenticate improvements of GDC-MTGO method over the conventional method.

1.2 Structure of manuscript

Manuscript is organized as: Section 2 appraisal the literature survey. Section 3 gives more explanation of GDC-MTGO method along with an architecture diagram. Section 4 explains the simulation settings. Section 5 explains comparative study of proposed model and conventional methods using various performance metrics. Lastly, Section 6 summarizes the manuscript.

LITERATURE REVIEW

Hybridization of Fox Optimization and Snake Algorithm was designed [16] to handle energy balancing and routing issues within heterogeneous network environments. However, the approach failed to consider various metrics, such as packet delivery and loss rate. A Stochastic PSO-based scheme was presented [17] for selecting the optimal route path. But the improvement of network performance and data transmission rate were major issues. The energy-efficient mega-cluster-basis of routing technique was presented [18] to improve the wide range of data transmission and extend the overall network lifetime. However, the data delivery time was not reduced.

The modified ACO algorithm was developed [19] for achieving successful delivery of data packets. But it failed to consider the clustering process to improve data delivery result with minimal delay. In [20], a SSA was designed to choose best CH selection for increasing packet delivery ratio. But it failed to consider energy harvesting method to improve efficient energy consumption as well as increase the network duration. A multi-objective binary Grey wolf optimizer was developed in [21] for finding optimal clustering to enhance the network lifetime. But it failed to apply the huge scale sensor network through bigger area coverage. The energy-efficient geographic (EEG) routing protocol was designed [22] depend on fuzzy logic to minimize delay and energy. But the data loss rate reduction was a major challenging issue.

An optimized energy-efficient protocol was designed in [23] for efficient CH selection depend on residual energy as well as distance metrics. An efficient technique was not considered to enhance CH selection, additional optimizing the energy effectiveness.

A bio-inspired ant-cuckoo algorithm was designed in [24]. But result comparison of proposed method through other conventional routing methods remained unaddressed to authenticate method. An adapted diffusion routing method was developed in [25] with the aim of significant energy savings. However result of packet delivery was not enhanced. An integration of Harris Harks Optimization Clustering through Fuzzy Routing method was developed [26] to enhance the throughput. However it failed to consider robustness-associated factors at constructing consistent clusters as well as routing paths. HPF-VS algorithm was designed in [27] with the aim of choosing CH and optimizing enduring energy. However, performance of delay was not analyzed.

Trust-based optimized clustered routing algorithm was designed in [28] for improving energy efficiency and network life span. However, the robustness of stability based routing remained unaddressed. Energy-effective multipath routing method was designed [29] to improve transmission reliability. But it failed to focus on applying the designed algorithm to dynamically changing network. A power-aware tree-basis of routing protocol was designed [30] for extending lifetime of network. But the designed protocol suffered from the scalability concerns in large-scale networks.

PROPOSAL METHODOLOGY

WSN often contains an enormous number of SN which cooperatively transmit the sensed information to sink node. As sensor nodes regularly functioned as battery-driven, efficient consumption of power is essential. Therefore, to expand life span of network, energy-efficient methods have to be adapted to collect and aggregate data. Depend on this motivation, new method named GDC-MTGO method is developed with different processes namely energy-efficient node clustering, cluster head selection, and routing.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

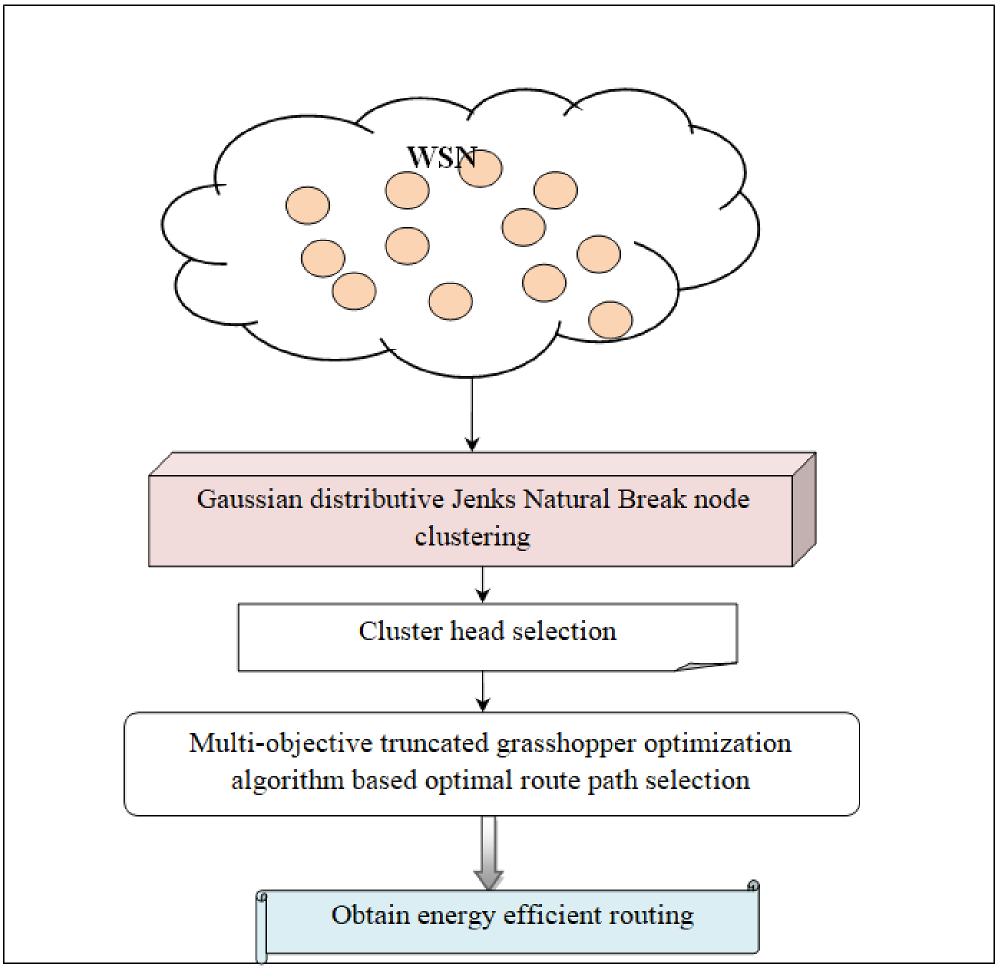

Figure 1. Architecture for the proposed GDC-MTGO technique

Figure 1 displays structural design of GDC-MTGO technique to attain energy-effective optimal data routing at WSN. The proposed GDC-MTGO method includes major processes namely clustering and optimal route path selection which follows numerous aims, comprising improved packet delivery rate, reduction of energy utilization thereby broadening life of network. First, Energy aware Jenks Natural Break Node Clustering is employed to divide sensor network to number of clusters. Second, optimal route paths among SN and CH are determined using Multi-objective Grasshopper Optimization based optimal roué path selection. These two processes are implemented into proposed technique to enhance result of routing process at WSN.

3.1 Network model

This section focuses on a WSN system with a bases station 'BS' associated to network. Network model is depicted in figure 2, contains arbitrarily allocated sensor nodes $SN_i = SN_1, SN_2, SN_3 \dots SN_n$in an $M \times M$ network area for sensing and collecting the data packets from an environment that has a similar sensible capacity and initial battery powers. First, the total network is partitioned to number of groups depend on their energy level 'EN'. Secondly, an energy-efficient cluster head is chosen $Ch_1, Ch_2, \dots, Ch_k$ that is accountable for gathering information from SN in cluster and transmitting to BS for further processing.

The proposed GDC-MTGO method first performs the clustering process to separation entire sensor network to number of clusters. In order to achieving this process, the proposed GDC-MTGO method employs the Jenks Natural Break Node Clustering based on a node energy level. Gaussian distributive Jenks Natural Break is a clustering approach used to discover the optimal grouping of sensor nodes into distinct categories. It aims to reduce the average

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

variation of energy values within each cluster from their respective mean while maximizing the differences between the means of different clusters. Major aim of proposed clustering method aims to minimize within-cluster variance as well as enhance between-cluster variance.

At first, every SN contains a comparable energy level. Due to sensing as well as examining nature of SN, the initial total energy gets degraded. Therefore, total sensor energy level is estimated as follows,

$$EN_{con}^{SN_i} = EN_S + EN_P + EN_{TX} \tag{1}$$

Where, $EN_{con}^{SN_i}$ indicates a energy consumption of i^{th} sensor node, EN_{TX} indicates an energy dispersed during transmission of a data, EN_P refers to an energy consumed during processing tasks, E_S denotes a energy consumption of sensing the data.

The remaining energy level of SN is computed depend on dissimilarity among total energy as well as the utilized energy level for sensing as well as observing environmental situations. Residual energy refers to the remaining energy of the node to perform its tasks. By tracking and monitoring the residual energy of SN, it becomes possible to estimate lifetime of sensor nodes. The computation of residual energy of node is computed as,

$$EN_{Res}^{SN_i} = TEN^{SN_i} - EN_{con}^{SN_i} \tag{2}$$

Where, $EN_{Res}^{SN_i}$ refers residual energy level of i'th SN, $EN_{Res}^{SN_i}$ indicates a total initial energy of 'i'th SN,$EN_{con}^{SN_i}$ denotes utilized energy of 'i'th SN. Energy level of sensor nodes determined in unit of Joule (J). Depend on estimated energy level, clustering process is executed as,

At first, numbers of clusters are initialized arbitrarily.

$$C_k = C_1, C_2, C_3 \dots . C_k \tag{3}$$

Where, C_k denotes a 'k' number of clusters. Afterward, mean (i.e. centroid) is measured for every cluster depend on their node energy level. Mean energy level across all 'n' nodes within the network represented as follows,

$$\mu_{EN}{}^{SN_i} = \frac{\sum_{i=1}^{n} EN_{Res\ i}^{SN_i}}{n} \tag{4}$$

Where $\mu_{EN}{}^{SN_i}$ denotes a mean of energy level of node is measured as ratio of sum of all node energy '$\sum_{i=1}^{n} EN_{Res\ i}^{SN_i}$' to total number of nodes 'n' in clusters. Then Jenks breaks clustering technique cluster nodes to dissimilar groups depend on their mean value by using Gaussian distribution function.

$$G = \frac{1}{\sqrt{2\mu\sigma}} \exp\left[-\sum_{i=1}^{n} \frac{\left(EN_{Res}^{SN_i} - \mu_{EN}{}^{SN_i}\right)}{2\sigma^2}\right] \tag{5}$$

Where G denotes a Gaussian distribution function, $EN_{Res}^{SN_i}$ denotes a residual energy of each SN, $\mu_{EN}{}^{SN_i}$ indicates mean of energy level of node, $\mu_{EN}{}^{SN_i}$ denotes mean, σ denotes a deviation. Based on the Gaussian distribution function values, SN are grouped to particular clusters. This process repetitive for every SN within network. Final clustering result reduces the variance within-cluster and maximizes the variance between the clusters. Like this, every sensor nodes are clustered to number of clusters based on mean and deviation. Lastly, CH is chosen to extend network lifetime as well as minimizing delay. Node that has superior residual energy within the cluster than other is chosen as cluster head.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Input: number of sensor nodes $SN_i = SN_1, SN_2, SN_3 \dots SN_n$
Output: Energy efficient clustering
Begin
Step 1: Distributes the number of sensor nodes $SN_i = SN_1, SN_2, SN_3 \dots SN_n$
Step 2: **For each node**
Step 3: **Compute** the energy level using (1) (2)
Step 3: **End for**
Step 4: **Initialize** 'k' number of clusters
Step 5: **for each cluster** 'k'
Step 6: Compute the mean value '${\mu_{EN}}^{SN_i}$' using (4)
Step 7: **End for**
Step 8: **for each mean** ${\mu_{EN}}^{SN_i}$
Step 9: **for each sensor node** 'SN'
Step 10: Measure the Gaussian distribution 'G' using (5)
Step 11: **End for**
Step 12: **End for**
Step 13: Group the sensor nodes based on 'G' into particular cluster
Step 14: **For each cluster do**
Step 15: Find sensor node with max 'G'
Step 16: Select cluster head 'CH'
Step 17: **End for**
Step 18: **Return** (clustering results)
End

Figure 2. Algorithm

Algorithm 2, described above, outlines the process of sensor node clustering based on energy levels. Initially, a number of SN are employed within network. For each node, energy level and residual energy are measured. After calculating the energy levels, proposed technique begins through randomly initializing number of clusters. Mean energy level for each cluster is computed. Gaussian distribution is applied to evaluate the deviation and association among energy levels of SN as well as their mean energy level. Subsequently, sensor nodes are grouped according to their energy levels. Finally, SN with maximum residual energy within each cluster is chosen as CH to enable efficient data transmission with minimal delay.

3.2 Multi-objective truncated Grasshopper Optimization for route path selection

Second procedure of GDC-MTGO technique is to discover an optimal route path for improving information delivery as of source to destination (i.e. base station). Path selection is the process of finding the best route from the multiple available routes to destination node by using different functions namely distance, energy, trust, link stability among cluster head in wireless networks. Therefore, the proposed GDC-MTGO method utilizes Modified Grasshopper Optimization to select the best route path. The grasshopper optimization is a meta-heuristic optimization and population-based swarm intelligence algorithm that emulates the biological characteristics such as finding the food sources in nature. In the proposed optimization algorithm, grasshoppers represent the search agents i.e. number of paths between the nodes whereas the food sources are the best positions of grasshoppers in the swarm i.e. optimal path.

First, the algorithm begins with the population generation phases where number of routing paths are initialized in search space. The populations of routing paths are generated as follows,

$$RP_r = RP_1, RP_2, \dots .. RP_q \quad \text{Where} \quad r = 1,2,3 \dots . q \tag{6}$$

Where, RP_r denotes a 'q' number of routing paths among source to BS. After initialization, the fitness is computed by considering the multiple objectives functions among cluster head and BS.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

First, distance among source and BS is measured. Let us consider the coordinate of source node represented as (x_1, y_1) and the base station denoted as (x_2, y_2) in a two-dimensional Cartesian system. Therefore, the Manhattan distance is measured as follows,

$$DS = |x_1 - x_2| + |y_1 - y_2| \tag{7}$$

Where, DS denotes a distance between source node as well as BS. Energy consumption over route path is determined depend on sum of energy consumed between consecutive nodes in the particular route path. It is mathematically expressed as follows,

$$EC\ [RP] = \sum_{k=1}^{M-1} EN\ [SN_k, SN_{k+1}] \tag{8}$$

$$EN\ [SN_i, SN_{i+1}] = EN_{el}.B + EN_{amp}.B.DS_{k,k+1} \tag{9}$$

From (8), $EC\ [RP]$ refers to energy consumption over the route path, $EN\ [SN_k, SN_{k+1}]$ indicates an energy consumed between consecutive nodes 'SN_k' and SN_{k+1} in the particular route path. From (9), EN_{el} indicates energy utilized through electronic circuitry during the transmission of solitary bit of information at communication, B denotes a size of the data packet being transmitted measured in bits, EN_{amp} indicates an energy consumed by the transmit amplifier, $DS_{k,k+1}$ distance between the consecutive nodes.

The Link stability is measured is measured as the duration of connection between the nodes along the route paths. The link stability is a significant parameter to minimize the packet drop and enhance the data packet transmission between the sources and destination.

The proposed optimization method effectively determines the better link stability among nodes depend on beacon message distribution to perform the continuous data distribution.

Initially, source node i broadcast beacon message to several another nodes i.e. cluster heads. The illustration of beacon message distribution is revealed in figure 3.

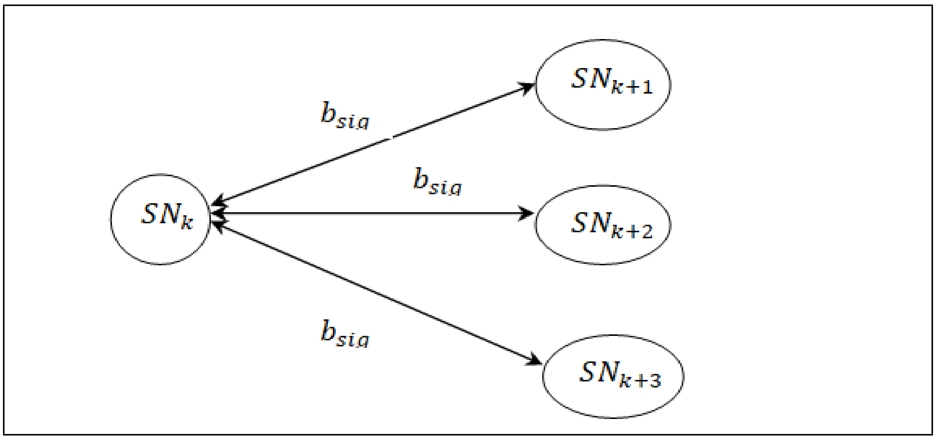

Figure 3. Beacon message distribution between the nodes

Figure 3 illustrates the distribution of the beacon message distribution between the sensor nodes. The probability of successful reception of beacon message is used to determine the link stability 'LS' between the nodes.

$$LS \rightarrow P = \left[\frac{b_{sig}(r)}{b_{sig}(t)}\right] \tag{10}$$

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

In (10),P denotes a probability of successful reception of beacon message, $b_{sig}(t)$ specifies the number of beacon message transmitted from source node 'Sn_k' and the other nodes ($Sn_{k+1}, Sn_{k+2}, Sn_{k+3}$), $b_{sig}(r)$ indicates a beacon message received at the source node 'Sn_k'. The probability value lies between 0 to 1. If the probability is higher, then the link between the node k and other node is stable at a time't'. Otherwise, the link is unstable. Followed by, fitness is estimated depend on multiple objective functions as given below,

$$F = \min(DS, EC\ [RP])\ \&\&\ \ max\ (LS) \tag{11}$$

Where, F symbolizes a fitness, min denotes minimize the distance 'DS', energy consumption of the route path '$EC\ [RP]$' $max\ (LS)$indicates maximum link stability between the nodes over the time 't'.

After that, Truncation selection is employed to determine the current best solutions from the populations based on the fitness evaluation. In the truncation selection process, the individual's grasshoppers or route paths are sorted into descending order based on the fitness.

$$RP_1 > \ RP_2 > \cdots > RP_q \tag{12}$$

From the sorted lists, smaller group of individuals are selected for minimizing the complexity of the algorithm. Followed by, the mathematical model of the swarming behavior of grasshoppers from the current best population is formulated based on the three factors such as social interaction 'SI_i', gravity force 'GR_i' and force of wind direction 'WD_i' of the i^{th} grasshopper.

$$P_i = SI_i + GR_i + WD_i \tag{13}$$

Where, P_i indicates a position of the i^{th} grasshopper.

$$SI_i = \sum_{r=1}^{S} H\ (\ DS_{rs}).\widehat{DS_{rs}} \tag{14}$$

Where, H denotes a strength of the social forces between the grasshoppers, DS_{rs} denotes a distance between the r^{th} and s^{th} grasshoppers $|X_s - X_r|$, $\widehat{DS_{rs}}$ denotes a unit vector ($\widehat{DS_{rs}} = \left(\frac{X_s - X_r}{DS_{rs}}\right)$.

$$GR_i = \ -gC_e \tag{15}$$

Where, g indicates a gravitational constant, C_e indicates a unit vector toward center of earth (i.e. 1).

$$WD_i = \ \delta D_w \tag{16}$$

Where, δ indicates a drift constant,D_w indicates a unit vector wind direction (i.e. 1). The above three factors are substituted in the equation (13) and get the position of the grasshoppers

$$P_i = \sum_{r=1}^{S} H\ (\ |X_s - X_r|).\left(\frac{X_s - X_r}{DS_{rs}}\right) - gC_e + \ \delta D_w \tag{17}$$

Therefore, the updated position of the grasshoppers is expressed as follows,

$$P^{new} = \varphi_c \left(\sum_{r=1}^{S} \varphi_c\ \frac{u-l}{2} H\ (\ |X_s - X_r|).\left(\frac{X_s - X_r}{DS}\right) + \ X_{best}\right) \tag{18}$$

$$\varphi_c = \varphi_{c_{max}} - \ C_{iter}\ \frac{\varphi_{c_{max}} - \varphi_{c_{min}}}{M_{iter}} \tag{19}$$

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Where, ${P_i}^{new}$ updated position of the grasshoppers, X_s and X_r denotes a position of the r^{th} and s^{th} grasshoppers, u and l denotes a upper and lower bound in the dimension, S denotes a number of grasshoppers, X_{best} denotes a best position of the grasshopper, φ_c indicates a coefficient, $\varphi_{c_{max}}$ denotes a maximum value, $\varphi_{c_{min}}$ indicates a minimum value, C_{iter} denotes a running iteration, M_{iter} denotes a maximum number of iterations. This procedure is frequent until algorithm achieves the maximum number of iterations. Finally, optimal route path is chosen from the population for broadcasting data packets. The flow process of the Multi-objective Grasshopper Optimization is given below.

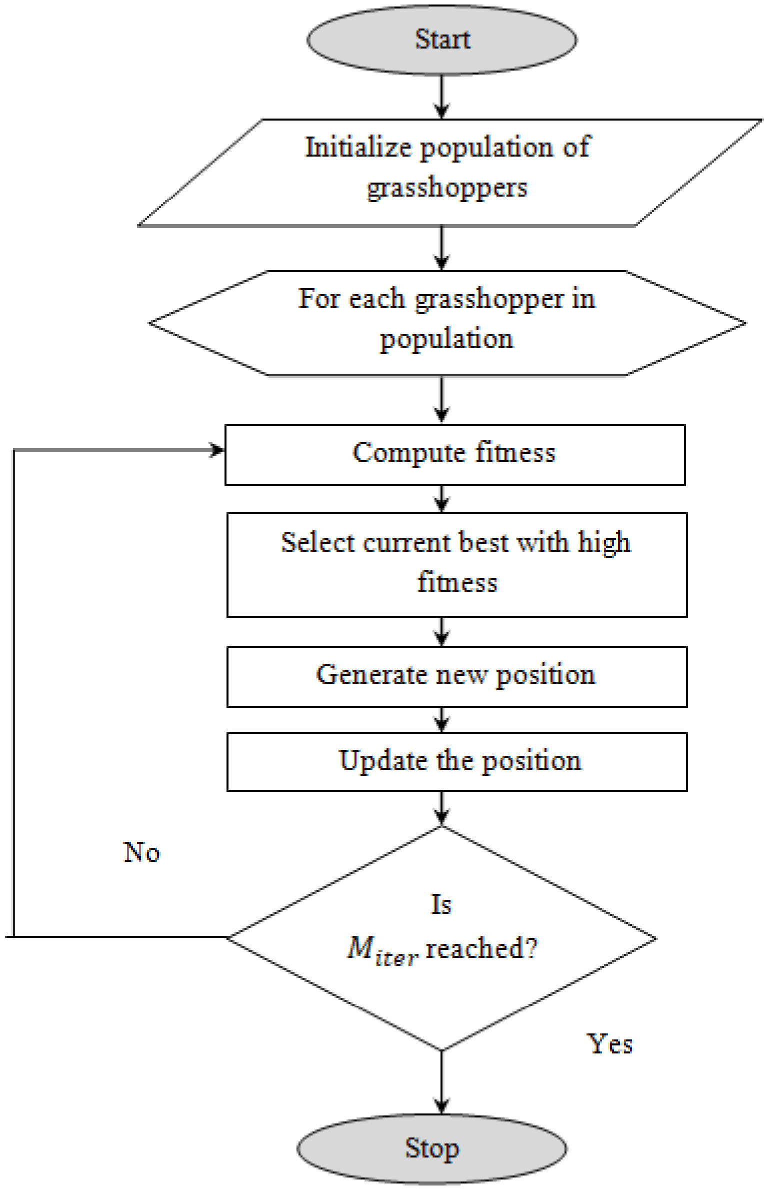

Figure 4. Flow Chart of Multi-objective truncated Grasshopper Optimization

Figure 4 given above depicts the flow diagram of the multi-objective truncated Grasshopper Optimization for selecting the optimal route path with minimum distance, energy consumption, and better link stability. As a outcome, then source node transmits information packets through optimally selected route paths. In this way, energy-efficient data forwarding is carried out in WSN. If any link malfunction occurs between cluster heads, proposed technique executes the route maintenance process and identifies another alternative optimal route path to improve the data delivery as well as minimize delay. The algorithmic process of the route path optimization is below.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

// **Algorithm 2: Multi-objective truncated Grasshopper Optimization**
Input: Number of clustered sensor nodes $SN_i = SN_1, SN_2, SN_3 \ldots SN_n$, data packets $Dp_1, Dp_2, Dp_3, \ldots Dp_n$
Output: improve data delivery
Begin
Step 1: Initialize the population of the route paths $RP_r = RP_1, RP_2, \ldots.. RP_q$
Step 2: **for each** route path in populations
Step 3: Estimate distance, energy consumption and link stability using (7) (8) (10)
Step 4: Compute the fitness 'F' using (11)
Step 5: **While** ($iter < M_{iter}$) **do**
Step 6; Select the current best using (12)
Step 7: Generate new position using (17)
Step 8: Update the position using (18)
Step 9 $iter = iter + 1$
Step 10: Go to step 5
Step 11: Obtain the optimal route path
Step 12: **End while**
Step 13: **End for**
Step 14: **If** route failure occurs **then**
Step 15: Select another optimal route path
Step 16: **End if**
End

Algorithm 2 described the outlines of various processing steps involved in optimal route path selection using multi-objective truncated grasshopper optimization in WSN. Number of clustered nodes is taken as input. Optimization technique begins with the population of route paths. For each path, distance, multi-objective functions are measured. Followed by, fitness is estimated depend on multi-objective functions. Afterward the truncated selection process is used for choosing current best solutions based on the fitness. After that, swarming behavior is estimated based on three factors and the position is updated. This entire process gets iterated until the algorithm reaches its maximum iterations. This iterative process enables the algorithm to identify the optimal route path. Finally, source node broadcast data packets along optimal route path. Finally, route maintenance process is carried out with the aim of achieving an improved data delivery and minimizes the delay.

SIMULATION SETUP

In this section, simulation of three different methods namely the proposed GDC-MTGO method models, an existing method referenced as SFO-SHO hybrid framework [1], and ECPF [2] are implemented using the NS3 simulator. A total of 500 SN are employed a square area of size ($1100\,m * 1100\,m$). Random Waypoint mobility model is employed to enable energy effective routing in WSN. Simulation time is set to 100 seconds. To facilitate energy efficient routing, DSR protocol is employed for optimal data delivery at WSN.

Table 1. Simulation Parameters

Simulation parameters	Value
Simulator	NS3
Network area	1100m * 1100m
Number of sensor nodes	50, 100, 150, 200…500
Number of data packets	100, 200, 300, ….1000
Protocol	DSR
Simulation time	100sec
Mobility model	Random Way Point model
Nodes speed	0-20m/s
Communication range of a sensor nodes	30m
Number of runs	10

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

PERFORMANCE ANALYSIS

This section gives a result comparison of three different methods namely GDC-MTGO method models, SFO-SHO hybrid framework [1], and ECPF [2]. Various evaluation metrics are used to evaluate performance of GDC-MTGO method and existing methods. The analyses of these metrics are summarized using both table and graphical representations.

Energy consumption: It is calculated as amount of energy utilized through SN during data packet routing. It is formulated as follows,

$$EC = \sum_{i=1}^{n} SN_i * EC\ (SN) \tag{20}$$

Where, EC indicates the overall energy consumption, 'n' denotes number of , $EC\ (SN)$ refers to a energy consumption for a single sensor node. Energy consumption measurement is expressed in joules (J).

Data packet delivery rate: It refers to ratio of number of data packets correctly received at BS to information sent from source node in WSN. It is measured as follows:

$$DPDR = \sum_{j=1}^{m} \left[\frac{DPR}{DP_j\ sent}\right] * 100 \tag{21}$$

Where $DPDR$ refers to a data delivery rate, DPR symbolizes the data packets correctly received at BS and $DP_j\ sent$ indicates a data sent. The ratio is calculated in percentage (%).

Data packet loss rate: It is calculated as ratio of number of data packets lost at BS to total number of data packet sent. It is measured as follows,

$$DPLR = \sum_{j=1}^{m} \left[\frac{DPL}{DP_j\ sent}\right] * 100 \tag{22}$$

Where $DPLR$ refers to a data packet loss rate , DPL represents the data packet lost at the destination and $DP_j\ sent$ represents a number of data packet sent. It is measured in percentage (%).

Throughput: it refers to a rate of successful data transmission over a communication network within a given period. It is calculated in bits per second (bps), based on scale of the network. Higher throughput shows better amount of data effectively broadcasted.

$$THP = \left[\frac{Succ\ \_Trans\_\ data\ packet\ (bits)}{time\ (s)}\right] \tag{23}$$

Where, THP indicates a throughput, $Succ\ \_Trans\_\ data\ packet\ (bits)$ denotes a successful transmission of data packets in bits in one seconds (Bps).

End to end delay: Delay is a key performance statistic that measures time it takes for information packets to travel as of source to destination across network. Lower the delay leads to faster data transfer.

$$E2ED = T_j(R) - T_j(T) \tag{24}$$

Where, $E2ED$denotes an End to end delay, $T_j(R)$ denotes time of j^{th}data packet received at destination, $T_j(T)$ denotes a time of j^{th}data packet transmitted from source. It is measured in milliseconds (ms).

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 2. *EC* versus number of sensor nodes

Number of sensor nodes	*EC* (Joule)		
	GDC-MTGO	SFO-SHO hybrid framework	ECPF
50	25	29	32.5
100	27	32	36
150	36	39	42
200	44	48	54
250	52.5	56.25	62.5
300	60	66	69
350	66.5	73.5	77
400	72	76	80
450	76.5	81	85.5
500	80	87.5	90

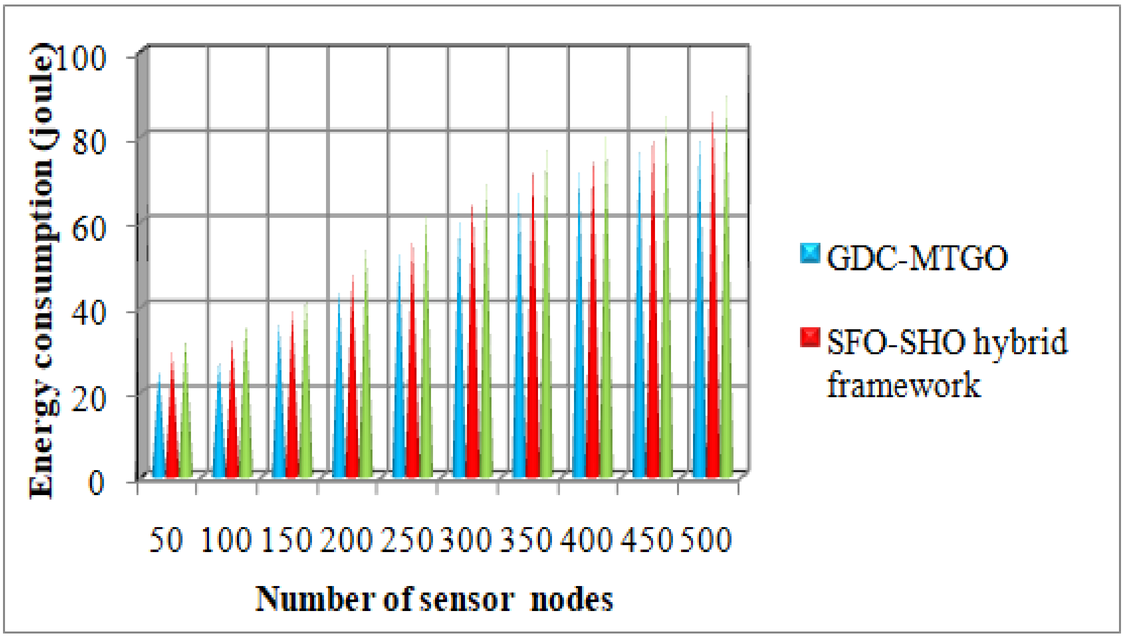

Figure 5. Graphical illustration of *EC*

Figure 5 demonstrates simulation outcomes of EC versus number of SN. According to obtained results, proposed GDC-MTGO method minimized performance of EC. Let us consider number of SN 50 in first run. By applying the GDC-MTGO method, 25$Joule$ of energy consumed through routing process. In comparison, EC of SFO-SHO hybrid framework [1] and ECPF [2] was found to be 29 $Joule$ and 32.5$Joule$ respectively. Various energy consumption results were obtained and compared. The comparison specifies that the GDC-MTGO method minimizes the energy consumption by 9% and 16% than the existing techniques. This is owing to relevance of the Gaussian distributive Jenks Natural Break Node clustering technique. The clustering technique considers number of SN as input. Afterward, every SN in WSN are grouped depend on their energy level by applying a Gaussian distribution function. For every cluster, the SN through superior residual energy are considered as CH. Routing process is carried out through the energy-efficient CH, outcoming in enhanced network lifetime by reducing EC.

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Table 3. *DPDR* versus number of data packets

Number of data packets	*DPDR* (%)		
	GDC-MTGO	SFO-SHO hybrid framework	ECPF
100	92	90	88
200	91.5	89	87.5
300	91.66	90.66	88.33
400	92	88.75	86.25
500	92.6	89	87.2
600	92.66	89.33	87.5
700	91.28	89.14	87.71
800	92.62	89.37	87.75
900	92.88	89.55	87
1000	92.5	89	87.2

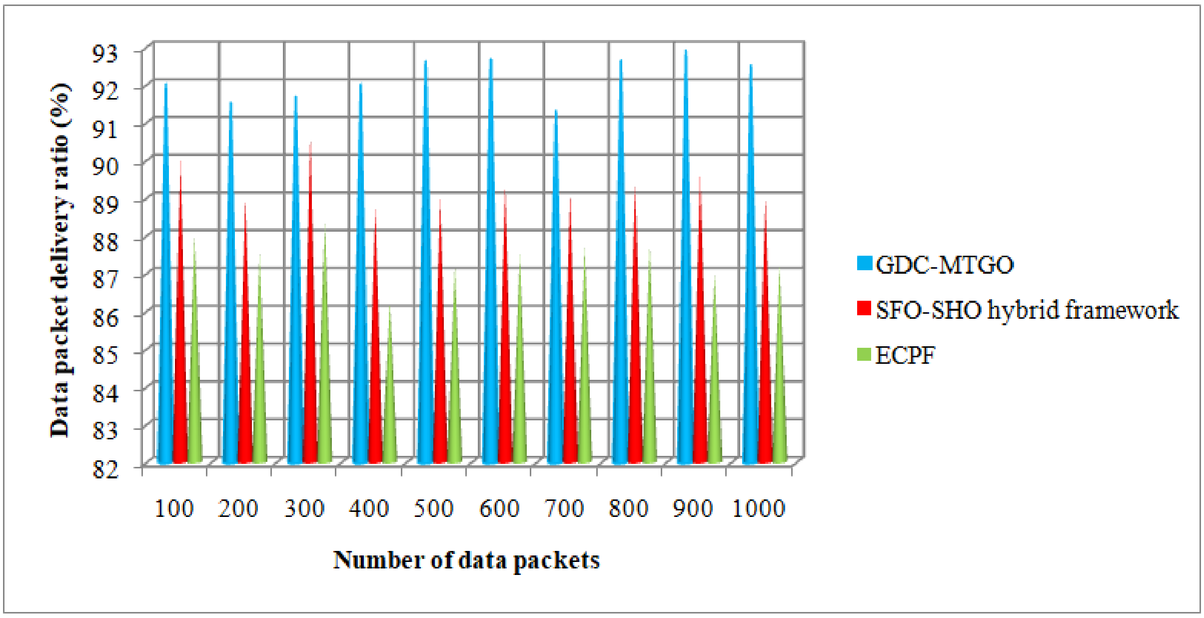

Figure 6. Graphical illustration of *DPDR*

Figure 6 depicts graphical analysis of *DPDR* plotted against number of data packets being sent from source to base station taken in the ranges from 100 to 1000. *DPDR* is calculated using three methods namely proposed GDC-MTGO method, SFO-SHO hybrid framework [1] and ECPF [2]. According to figure 6, the *DPDR* of the proposed GDC-MTGO method displays a significant development in routing performance analysis compared to other techniques. This improvement is achieved by relevance of multi-objective truncated grasshopper optimization algorithm for routing the data packets. In optimization process, the population of available route paths between source and base station are initialized compute the fitness based on the multi-objective functions. Truncated selection process is used to choose the global best optimal path. Based on this analysis, route path with better link stability are selected to improve data delivery. A total of ten runs were conducted for each method, and the overall results were compared. Overall comparison outcomes shows *DPDR* of SFO-SHO hybrid is enhanced by 3% and 5% than the existing methods [1] and [2].

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 4. *DPLR* versus number of data packets

Number of data packets	*DPLR* (%)		
	GDC-MTGO	SFO-SHO hybrid framework	ECPF
100	8	10	12
200	8.5	11	12.5
300	8.33	9.33	11.66
400	8	11.25	13.75
500	7.4	11	12.8
600	7.33	10.66	12.5
700	8.71	10.85	12.28
800	7.37	10.62	12.25
900	7.11	10.44	13
1000	7.5	11	12.8

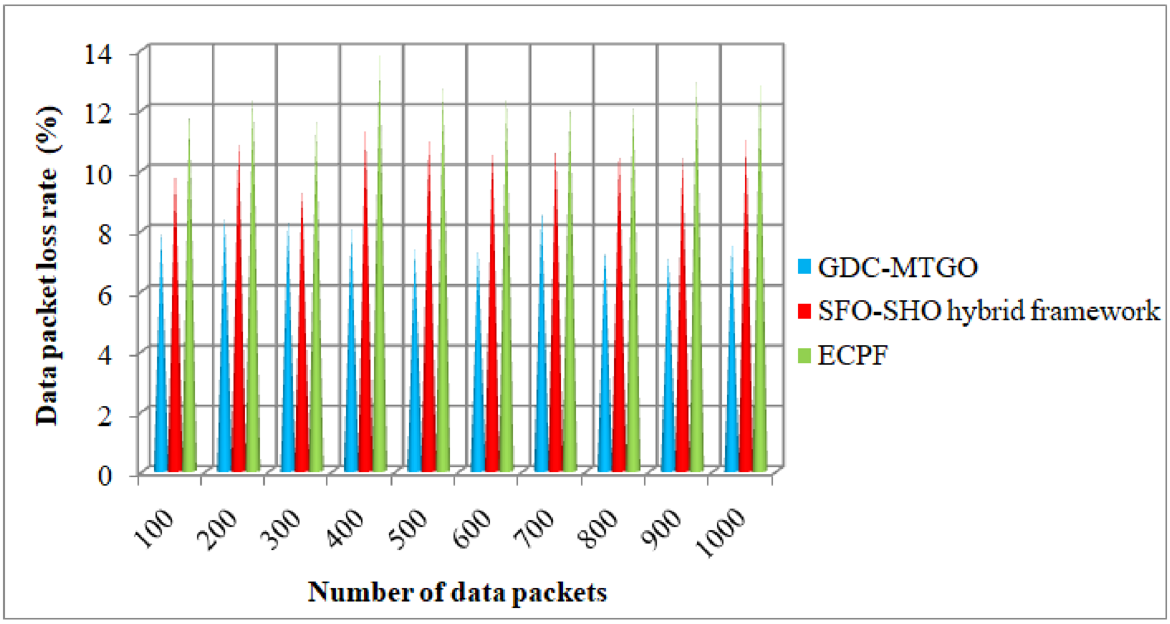

Figure 7. Graphical illustration of *DPLR*

The performance outcomes of *DPLR* versus number of data packets are depicted in figure 7 for GDC-MTGO method, SFO-SHO hybrid framework [1] and ECPF [2]. In figure 7, *DPLR* the GDC-MTGO method outperforms others by achieving a considerably minimal data loss rate during the routing process between sources to the base station in WSN. This is because of the GDC-MTGO method efficiently select energy-efficient sensor nodes for routing the data packets. Additionally, ensures optimal route path identification which further enhances data delivery and minimizes the data loss. Considering 100 data packets, GDC-MTGO method achieved a data packet loss rate of 8%, whereas existing methods [1] and [2] obtained 10% and 12%, respectively. Likewise, various performances were observed across all the three methods. The results of the GDC-MTGO method are compared to outcomes of conventional techniques. Average of ten outcomes illustrates GDC-MTGO method minimizes *DPLR* by 26% and 37% than the [1] and [2], respectively

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 5. Throughput versus data packets sizes

Data packet size (KB)	Throughput (bps)		
	GDC-MTGO	SFO-SHO hybrid framework	ECPF
100	187	165	142
200	274	242	187
300	478	362	234
400	524	412	365
500	675	542	417
600	812	674	514
700	1045	886	648
800	1136	1026	975
900	1428	1124	1021
1000	1745	1324	1136

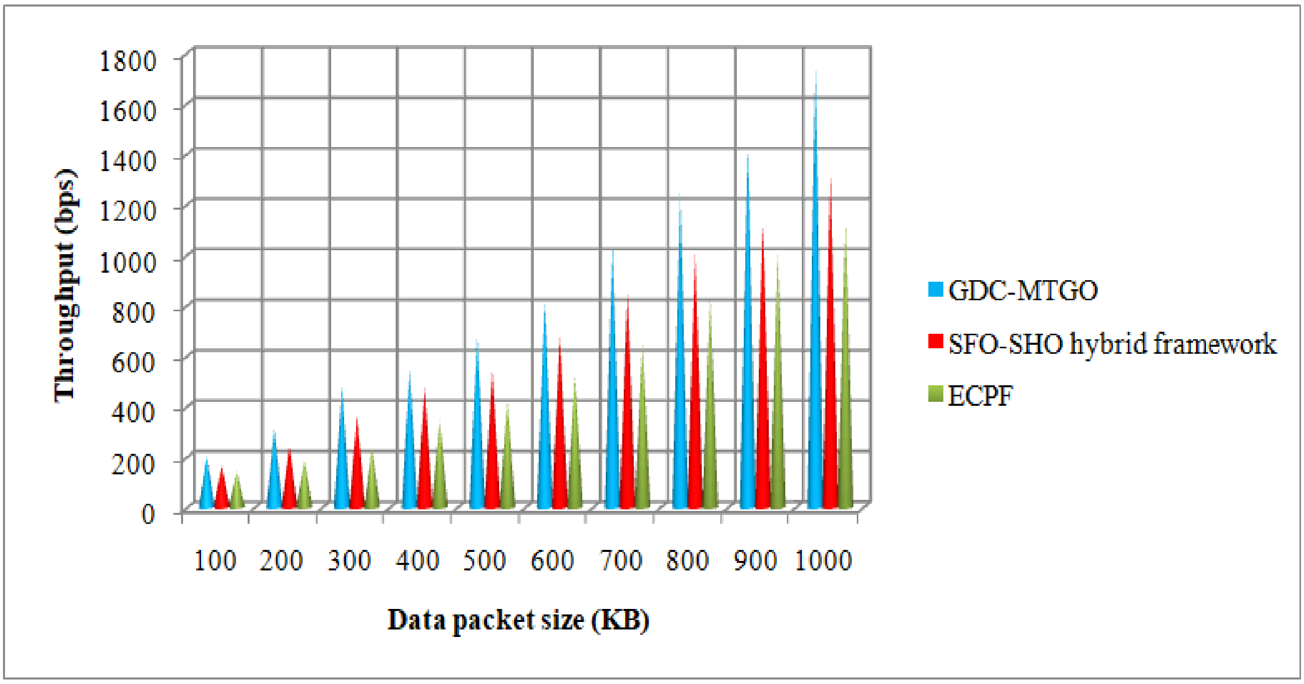

Figure 8. Graphical depiction of throughput

Figure 8 demonstrates performance outcomes of throughput versus size of data packet being sent from the source to BS. Along with observed outcomes, GDC-MTGO technique increased performance of the throughput during the data packet routing. Let us consider a data size of 100KB being transmitted from the source node. By applying the GDC-MTGO method, $187KB$ of data packet is received at the destination. Similarly, throughput of [1] and [2] were found to be $165bps$ and $142bps$, respectively. Different throughput performance were attained and compared. Overall comparison outcomes designates GDC-MTGO method increases performance of throughput by 25% and 60% than the existing techniques. This enhancement is attained because GDC-MTGO method performs the route maintenance process when the link failure occurred between the nodes. In this process, the GDC-MTGO method selects another optimal route path for continuous routing the data packets, resulting in enhanced network throughput.

Table 6. *E2ED* versus number of data packets

Number of data packets	*E2ED* (ms)		
	GDC-MTGO	SFO-SHO hybrid framework	ECPF
100	12.3	15	17.5
200	14.8	17.2	20.3
300	17	19	22
400	19.6	23	25
500	23.3	26	27.4
600	26.7	28	31.2
700	28.5	32	34.5
800	31	34	36
900	33.5	36	38
1000	35.2	37.8	39

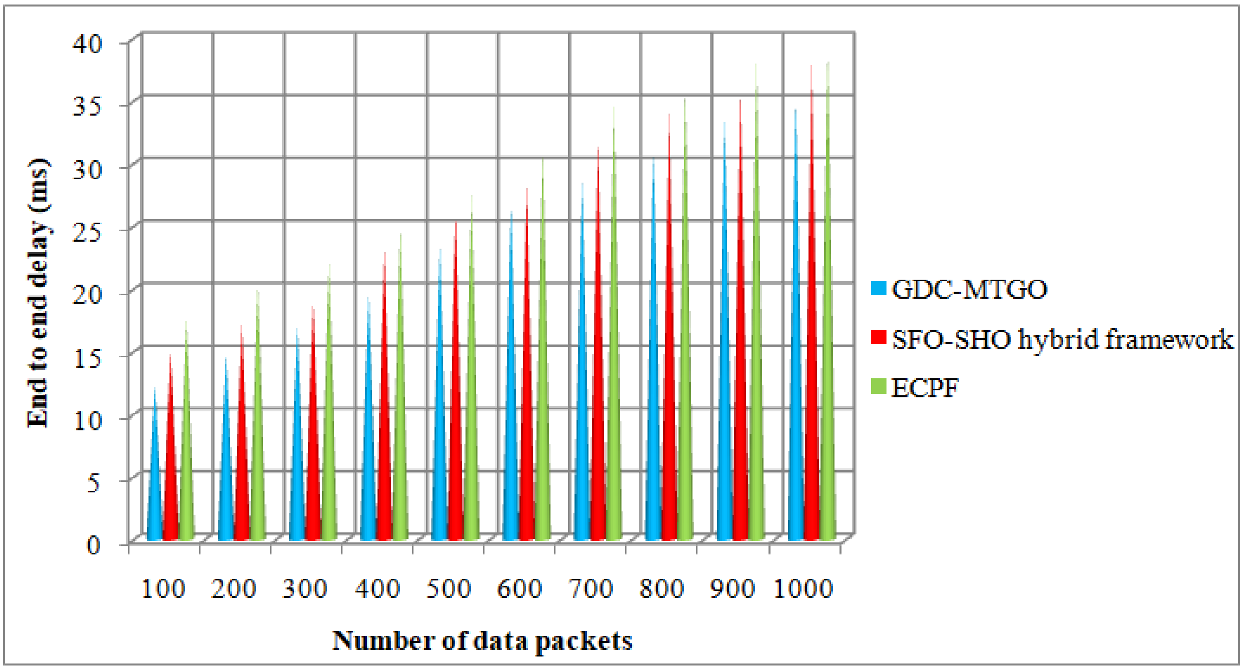

Figure 9. Graphical illustration of *E2ED*

The simulation results depicted in figure 9 above represents the performance outcomes of $E2ED$in energy efficient routing. In figure 8, number of data packets is considered in 'x' direction and $E2ED$performance outcomes were observed at 'y' axis. The observed results of the proposed GDC-MTGO method shows superior result in minimizing $E2ED$through routing process compared to conventional methods. In Figure 7, it is evident that $E2ED$increases for all three methods as number of data packets increases. However, GDC-MTGO method exhibits minimized $E2ED$from source to base station. In a simulation involving 100 data packets, the GDC-MTGO method consumed 12.3ms delay, while existing methods [1] and [2] consumed 15ms and 17.5ms, respectively. This improvement is achieved by enhancing the link stability between the nodes to ensure continuous data delivery. This process reduces the delay of

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

routing the data packets in WSN. The observed result confirms that the proposed GDC-MTGO method compared to existing methods. The average evaluation results demonstrate that $E2ED$in data transmission is minimized using the GDC-MTGO technique by 11% and 18% than the [1],[2] respectively.

CONCLUSION

Energy effective routing in WSN is meant to find optimal path for efficient data delivery with minimal delay. To achieve this objective, a novel GDC-MTGO method has been employed in this paper. Initially, the GDC-MTGO method undergoes Gaussian distributive Jenks Natural Break Node clustering technique for grouping he sensor nodes based on energy, resulting in improved network lifetime and minimized energy utilization. Subsequently, the multi-objective truncated grasshopper optimization algorithm is employed in WSN detect the optimal route path for routing data packets. This assists enhance data delivery as well as reduce packet loss rate. Manuscript conducts a simulation assessment using various parameters. Examined outcome confirms GDC-MTGO method outperforms existing methods, achieving a higher delivery rate, throughput while minimizing loss rate, energy consumption. Furthermore, the GDC-MTGO method proves to be efficient in minimizing $E2ED$ compared to conventional approaches.

REFERENCES

[1] Michaelraj Kingston Roberts, Jayapratha Thangavel, Hamad Aldawsari, "An improved dual-phased meta-heuristic optimization-based framework for energy efficient cluster-based routing in wireless sensor networks". Alexandria Engineering Journal, Elsevier, Volume 101, 2024, Pages 306-317. https://doi.org/10.1016/j.aej.2024.05.078

[2] Chang Lei, "An energy-aware cluster-based routing in the Internet of things using particle swarm optimization algorithm and fuzzy clustering", Journal of Engineering and Applied Science, Springer, Volume 71, 2024, Pages 1-25. https://doi.org/10.1186/s44147-024-00464-0

[3] Huangshui Hu, Xinji Fan & Chuhang Wang, "Energy efficient clustering and routing protocol based on quantum particle swarm optimization and fuzzy logic for wireless sensor networks", Scientific Reports, volume 14, 2024, Pages 1-19. https://doi.org/10.1038/s41598-024-69360-0

[4] N. Meenakshi, Sultan Ahmad, A. V. Prabu, J. Nageswara Rao, Nashwan Adnan Othman, Hikmat A.M. Abdeljaber, "Efficient Communication in Wireless Sensor Networks Using Optimized Energy Efficient Engroove Leach Clustering Protocol", Tsinghua Science and Technology , Volume 29, Issue 4, 2024, Pages 985 – 1001. **DOI:** 10.26599/TST.2023.9010056

[5] Halimjon Khujamatov, Mohaideen Pitchai, Alibek Shamsiev, Abdinabi Mukhamadiyev and Jinsoo Cho, "Clustered Routing Using Chaotic Genetic Algorithm with Grey Wolf Optimization to Enhance Energy Efficiency in Sensor Networks", Sensors, Volume 24, Issue 13, Pages 1-18. https://doi.org/10.3390/s24134406

[6] Zhen Wang , Jin Duan and Pengzhan Xing, "Multi-Hop Clustering and Routing Protocol Based on Enhanced Snake Optimizer and Golden Jackal Optimization in WSNs", Sensors ,Volume 24, Issue 4, 2024, Pages 1-22. https://doi.org/10.3390/s24041348

[7] Hongzhi Wang, Ke Liu, Chuhang Wang and Huangshui Hu, "Energy-Efficient, Cluster-Based Routing Protocol for Wireless Sensor Networks Using Fuzzy Logic and Quantum Annealing Algorithm", Sensors, Volume 24, Issue 13, 2024, Pages 1-22. https://doi.org/10.3390/s24134105

[8] Vivek Pandiya Raj, M. Duraipandian, "An energy-efficient cross-layer-based opportunistic routing protocol and partially informed sparse autoencoder for data transfer in wireless sensor network", Journal of Engineering Research, Elsevier, Volume 12, Issue 1, 2024, Pages 122-132. https://doi.org/10.1016/j.jer.2023.10.023

[9] Ramasubbareddy Somula, Yongyun Cho and Bhabendu Kumar Mohanta , "SWARAM: Osprey Optimization Algorithm-Based Energy-Efficient Cluster Head Selection for Wireless Sensor Network-Based Internet of Things", Sensors, Volume 24 , Issue 2, 2024, Pages 1-19. https://doi.org/10.3390/s24020521

[10] Le Yang, Damin Zhang, Lun Li & Qing He, "Energy efficient cluster-based routing protocol for WSN using multi-strategy fusion snake optimizer and minimum spanning tree", Scientific Reports, Volume 14, 2024, Pages 1-24. https://doi.org/10.1038/s41598-024-66703-9

[11] S. Sebastin Suresh, V. Prabhu, V. Parthasarathy, G. Senthilkumar, Venkateswarlu Gundu, "Intelligent data routing strategy based on federated deep reinforcement learning for IOT-enabled wireless sensor networks", Measurement: Sensors, Elsevier, Volume 31, 2024, Pages 1-9. https://doi.org/10.1016/j.measen.2023.101012

[12] Seemab Karim, Kashif Naseer Qureshi, Ashraf Osman Ibrahim, Anas W. Abulfaraj, Kayhan Zrar Ghafoor, "Enhanced centroid-based energy-efficient clustering routing protocol for serverless based wireless sensor networks", Journal of King Saud University - Computer and Information Sciences, Elsevier, Volume 36, Issue 5, 2024, Pages 1-15. https://doi.org/10.1016/j.jksuci.2024.102067

[13] Hassan Al-Mahdi , Mohamed Elshrkawey , Shymaa Saad , and Safa Abdelaziz, "An Intelligent Energy-Efficient Data Routing Scheme for Wireless Sensor Networks Utilizing Mobile Sink", Wireless Communications and Mobile Computing, Wiley, Volume 2024, Issue 1 , March 2024, Pages 1-20. https://doi.org/10.1155/2024/7384537

[14] Hongzhang Han, Jun Tang, Zhengjun Jing, "Wireless sensor network routing optimization based on improved ant colony algorithm in the Internet of Things", Heliyon, Volume 10, Issue 1, 15, 2024, Pages 1-16. https://doi.org/10.1016/j.heliyon.2023.e23577

[15] Mingyu Li, Jihang Yin, Yonggang Xu, Gang Hua, Nian Xu, "An Adaptive Energy-Efficient Uneven Clustering Routing Protocol for WSNs", IEICE Transactions on Communications, Volume E107-B, Issue 2, 2024, Pages 296 – 308. **DOI:** 10.23919/transcom.2023EBP3097

[16] P. Vijayaragavan, V Saravanan, Chalumuru Suresh, Manikavelan D, A. Maheshwari, K. Vijayalakshmi, Roman Hrbac , Lukas Demel, Vaclav Kolar, Narayanamoorthi, "FOAEAUC-SARP: A novel energy-efficient protocol integrating unequal clustering and intelligent routing for sustainable wireless sensor networks", Results in Engineering, Elsevier, Volume 25, 2025, pages 1-11. https://doi.org/10.1016/j.rineng.2024.103806

[17] Mamta Mann & Rishipal Singh, "Optimized stochastic particle swarm optimization integrated ranked backoff medium access control for optimal route selection in wireless sensor networks", Peer-to-Peer Networking and Applications, Springer, Volume 18, 2025, Pages 1–17. https://doi.org/10.1007/s12083-024-01837-1

[18] Bhaskar Prince, Prabhat Kumar & Sunil Kumar Singh, "Multi-level clustering and Prediction based energy efficient routing protocol to eliminate Hotspot problem in Wireless Sensor Networks", Scientific Reports, volume 15, 2025, Pages 1-21. https://doi.org/10.1038/s41598-024-84596-6

[19] Yasameen Sajid Razooqi, Muntasir Al-Asfoor, Mohammed HamzahAbed, "OptimiseEnergy Consumption of Wireless Sensor Networks by using modified Ant Colony Optimization", Acta Technica Jaurinensis, Volume 17, Issue 3, 2024, Pages 111–117. https://doi.org/10.14513/actatechjaur.00742

[20] Ghalib H. Alshammri, "Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm", Artificial Intelligence Review, Springer, Volume 58, 2025, Pages 1-32. https://doi.org/10.1007/s10462-024-11088-4

[21] Raju Pal, Mukesh Saraswat, Sandeep Kumar, Anand Nayyar & Pushpendra Kumar Rajput, "Energy efficient multi-criterion binary grey wolf optimizer based clustering for heterogeneous wireless sensor networks", Soft Computing, Springer, Volume 28, 2024, Pages 3251–3265. https://doi.org/10.1007/s00500-023-09316-0

[22] Kalavagunta Aravind, Praveen Kumar Reddy M, "Optimized Fuzzy Logic Based Energy-Efficient Geographical Data Routing in Internet of Things", IEEE Access , Volume 12, 2024, Pages 18913 – 18930. **DOI:** 10.1109/ACCESS.2024.3354174

[23] Lalit Kumar Tyagi, and Anoop Kumar, "OEE-WCRD: Optimizing Energy Efficiency in Wireless Sensor Networks through Cluster Head Selection Using Residual Energy and Distance Metrics", EAI Endorsed Transactions on Scalable Information Systems, Volume 11, Issue 5 2024, Pages 1-10. https://doi.org/10.4108/eetsis.4268

[24] Lucia K. Ketshabetswe , Adamu Murtala Zungeru , Caspar K. Lebekwe , Bokani Mtengi, "A compression-based routing strategy for energy saving in wireless sensor networks", Results in Engineering, Elsevier, Volume 23, 2024, Pages 1-11. https://doi.org/10.1016/j.rineng.2024.102616

[25] Gad Hakim, Robin Braun and Justin Lipman, "Adapted Diffusion for Energy-Efficient Routing in Wireless Sensor Networks", Electronics, Volume 13, Issue 11, 2024, Pages 1-14. https://doi.org/10.3390/electronics13112072

Journal of Information Systems Engineering and Management
2025, 10(44s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[26] Di Jing, "Harris Harks Optimization Based Clustering With Fuzzy Routing for Lifetime Enhancing in Wireless Sensor Networks", IEEE Access, Volume 12, 2024, Pages 12149 – 12163. **DOI:** 10.1109/ACCESS.2024.3354276

[27] Haewon Byeon, Santosh Kumar, Divya Mahajan, K. Haribabu, M. Sivaprakash, Harshal Patil f , J. Sunil, "A hybrid path finder-based vortex search algorithm for optimal energy-efficient node placing and routing in UWSN", Results in Control and Optimization, Elsevier, Volume 14, 2024, Pages 1-14. https://doi.org/ 10.1016/j.rico.2024.100379

[28] S. Suresh Babu, N. Geethanjali, "Lifetime improvement of wireless sensor networks by employing Trust Index Optimized Cluster Head Routing (TIOCHR)", Measurement: Sensors, Elsevier, Volume 32, 2024, Pages 1-8. https://doi.org/10.1016/j.measen.2024.101068

[29] Feng Dan, Yajie Ma , Wenqi Yin, Xian Yang, Fengxing Zhou, Shaowu Lu and Bowen Ning, "An Accuracy-Aware Energy-Efficient Multipath Routing Algorithm for WSNs", Sensors, Volume 24, Issue 1, 2024 , Pages 1-21. https://doi.org/10.3390/s24010285

[30] V.Rama Krishna, Vuppala Sukanya, Mohd Abdul Hameed, "Enhancing Wireless Sensor Network lifetime through hierarchical chain-based routing and horizontal network partitioning techniques", Measurement: Sensors, Elsevier, Volume 36, 2024, Pages 1-11. https://doi.org/10.1016/j.measen.2024.101300