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Fog computing-based deep learning model for optimization of microgrid-connected WSN with load balancing

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Abstract
The advancement of power grids leads to the concept of the microgrid. Microgrids are placed at the end of an entire grid-connected system. Wireless sensor networks (WSNs) are engaged in the management of power generation, electricity consumption, and power transmission and distribution. In power generation, WSNs detect the amount of power generated that is managed by a microgrid for large-scale applications. Also, a WSN needs to monitor the microgrid's transmission status for effective transmission of power. To overcome these challenges, this research aimed to incorporate a fog computing network for the optimization of a microgrid-connected WSN. In a grid-connected community (GCC), an energy model was developed to evaluate the energy and performance of microgrids with a WSN. The constructed FGWHO fog computing-based model was used to estimate the microgrid distance, power generation, and power demand within the network. Based on the collected information, the whale optimization algorithm was used to calculate the optimal values required for data transmission. The optimization model estimated the optimal distance, energy, and communication of the microgrids. These facilitated the reduced energy utilization and improved the throughput and the PDR of the grid-connected WSN.

Keywords Grid Network · WSN · Whale optimization · Edge computing · Energy

1 Introduction

In sustainable development, energy and environmental factors are considered significant factors that affect renewable energy systems [1]. Faced with the multiple pressure of energy, environment, population, and climate, the exploitation, and utilization of renewable resources has become inevitable for the future development of power energy structures. Microgrids (MG) continue to attract attention as an effective supplement to conventional power operation [2]. MG economic dispatch [3] is one of the crucial issues related to MG system operation. A large number of domestic and international researchers have paid attention to the role of MG in electricity generation. To address the randomness of renewable energy resources in MG, model predictive control, along with robust optimization approaches, is applied to solve the economic dispatch optimization model which considers the uncertainty of MG [4, 5]. The investment and operation costs of wind turbines, photovoltaic (PV) systems, energy storage (ES) systems, and other distributed power sources in MG have been studied with decentralized algorithms and heuristic algorithms, respectively [6].

Microgrids utilize numerous communication media for transmission of information, such as power carriers in line, optical fiber, field bus, and wired communication medium. Even though MG is efficient and environmentally friendly, its medium of transmission is limited. MG exhibits certain limitations such as minimal flexibility, reduced expandability, and increased operational and maintenance costs. Recently, wireless communication technology has been developed for broader communication in power systems. In

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power generation systems, wireless sensor networks are deployed for MG power distribution, transmission and generation, and electricity consumption [7]. In a power generation process, a WSN evaluates the process in a generation unit and detects the malfunctioning unit for performance and security enhancement. In a power transmission process, the WSN monitors the transmission line and ensures secure operation. For power distribution, the WSN locates the faults in the distribution network for increased stability and higher accuracy. Finally, in power consumption, the WSN monitors parameters like current, real-time load and voltage. Based on this, we see that WSNs offer different prospects in MGs [8]. To achieve improved network performance, WSNs need to be more flexible and adaptive for appropriate routing and recovering processes.

Several sensor nodes are deployed in a larger coverage area and coordinate other nodes in an ad-hoc network. A WSN has certain constraints such as a limited communication range and increased capacity of data transmission. A WSN node gains energy from batteries and is placed in a hazardous environment, showing that the energy source is not sufficient. The deployed sensor node collects information about the area in which it is deployed and exchanges this information through a single hop or multihop for communication [9]. Even though several mechanisms are developed for WSN routing and optimization, they have not been promising enough.

1.1 Contribution of research

To overcome the limitation associated with multi-hop communication different routing and optimization techniques are evolved. However, those techniques are subjected to challenges associated with routing and energy. To withstand those challenges this research presented a following contribution those are stated as follows:

1. This paper developed a fog computing-based optimization technique for a grid-connected WSN.
2. The developed model incorporates the whale optimization technique for the estimation of the energy level in the WSN.
3. Using the proposed model, we boosted the residual energy of the nodes in the grid-connected system. Simulation results showed that the proposed FGWHO exhibited improved throughput, PDR and residual energy.

The paper is organized as follows: Sect. 1 gives a general description of the grid-connected WSN. In Sect. 2, the existing literature related to grid WSN is reviewed. Sections 3 and 4 describe the proposed technique. The simulation results of the proposed FGWHO are presented in Sect. 5, followed by the overall conclusion in Sect. 6. In Table 1 list of notation adopted are presented.

2 Related works

WSN is broadly applied in a vast range of applications due to its significant advantage. Some studies have examined WSN technologies and applications based on their power levels. Conventional technologies utilize grid-connected networks for effective communication and provision of reliable, efficient, clean and economic power grid systems in MG components such as distributed power generation stations, transmission lines, intelligent terminals and transformers. Wireless communication is a widely applied technology in MG communication systems. WSN minimizes the cost of operation, optimizes management and increases the stability of an MG. The incorporation of WSNs in MGs has its limitations, such as reduced lifetime and increased malfunction during routing, which increases the attention.

In [10] concentrated on CAN bus and ZigBee control system with MG for information collection and operation in the deployed area. It concentrated on detection of node malfunction in the deployed area.

In [11] concentrated on WSN routing mechanism for power systems integrated with digital communication networks. It integrates both wired and wireless communication media for MG data transmission with WSN. In [12] evaluated heterogeneous WSN (HWSN), with nodes in three different scenarios considered, such as sensor nodes (SNs), cluster heads (CHs) and sink nodes. The SNs were deployed either manually or randomly for data collection

Table 1 List of notation

Notation	Description
t	Iteration
A and C	Vector Coefficient
X	Position of Vector
r	Radius of sensor
$G(P)$	Routing Probability of nodes
p	Probabilistic value of nodes
p_0	Threshold probability of nodes
p_{avg}	Mean Value
$2\sigma^2$	Variance
ρ	Number transmitted packet
λ	Factors
$E(N)$	Energy of Nodes
Resi_LifeTime	Residual Lifetime of No
p_{actual}	Actual Communication range of nodes

and monitoring, with selection of CHs by a wireless medium. The CHs aggregated the local data and connected the sink nodes for communication. The sink nodes were involved in the transmission of data to the physical medium for information exchange. To maintain appropriate energy savings, the SNs were classified into several groups of clusters. Generally, CHs incorporate higher energy and longer communication in SNs. CHs interconnects sink nodes using multi-hop or single-hop communication. In [13] proposed a routing mechanism for WSN with the low-energy adaptive clustering hierarchy (LEACH) algorithm. The LEACH algorithm was involved in the selection of sensor nodes as CHs selection probability. In some cases, CHs with minimal energy were elected and defined as hot nodes. Those nodes led to node failure with reduced WSN lifetime. In [14] developed a routing algorithm integrated with GA for data aggregation through relay and sensor nodes. The genetic algorithm-based routing (GAR) was used to evaluate data transmission. The GAR was involved in the discovery of routes through the relay nodes between the BS, for distance and energy reduction, with the reduction of the data diffusion process between sender and receiver. In [15] developed a COCA for clustering for minimization of energy consumption. The clustering incorporated various clusters, with different unit areas considered and the distance between sink nodes reduced.

In [16] proposed a UCA clustering algorithm for construction of clusters within a specified geographical distribution. A PSO-based routing and clustering scheme was included for efficient energy routing. In [17] developed an optimization algorithm for PSO fitness evaluation and to estimate the hopping distance between sensors. The energy sensor was concentrated on the CH routing scheme for fault tolerance with an effective routing mechanism.

3 Network model

In MGs, networks transmit information through cables for long-distance communication. WSNs are based on power generation, consumption and distribution for all types of communication. A wireless communication medium is utilized at the edge of the computing network with a large sensor node incorporated. The sensor deployment should adopt two principles for effective coverage and transmission. The sensor node needs to incorporate several power lines, electrical appliances and equipment. The WSN area needs to guarantee minimal cost for data transmission. [18, 19] In MG, sensor networks are distributed with appropriate functional and structural characteristics for smooth data transmission. The WSN integrated with MG is constructed with an edge computing network with a tree structure. In Fig. 1 overall architecture of fog computing WSN model is presented.

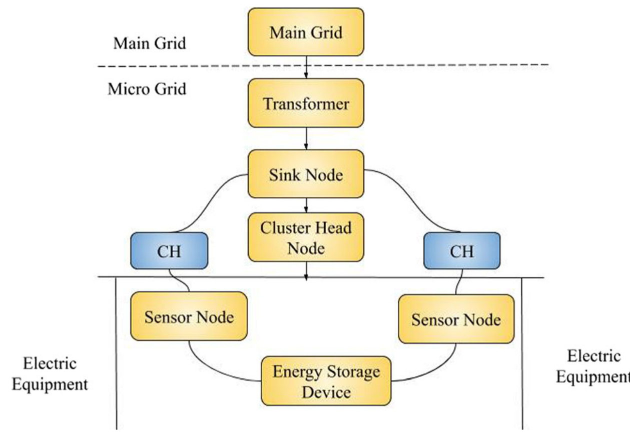


Fig. 1 Overall architecture of fog network

The microgrid connected with main grid relative independent characteristics with grid connected edge computing technology. In an MG, there are one bus and two feeders for different generation stations. The sensor nodes are equipped for status monitoring and fault detection. There are different energy storage devices with redundant power and different electrical equipment for power consumption. The user device sensor nodes are involved in automatic meter reading and feedback electricity price in a real-time environment. The power line sensor node is involved in the monitoring of current, voltage, etc. Every feeder incorporates several cluster heads and sensor nodes for cluster construction. The sensor node aggregates data with a cluster head and transmits sink node information. The sensor node is deployed randomly with the cluster head for data flow between the sensor and sink node.

3.1 Routing with Whale optimization

Whales are mostly considered predators. Based on this consideration, the mathematical model for the meta-heuristics approach was developed and its performance is presented:

3.1.1 Encircling prey

Humpback whales were able to locate the prey and encircle them, due to an unknown character of search space. Based on this consideration, the target prey position of the agent can be presented as given in Eqs. (1) and (2):

$$\tilde{D} = \left| C\vec{X}(t) - X(t) \right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A} \cdot \vec{D} \tag{2}$$

where, present iteration is defined as t, A and C are coefficient vectors, X defines the significant solution for identification of vector position.

This vector can be measured using Eqs. (3) and (4) as follows [20],

$$\vec{A} = 2\,\vec{a}\,.\,\vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\,\vec{r} \tag{4}$$

In above equation a decreases linearly concerning iteration count. The exploration phase was evaluated.The routing approach with multi-path was involved in the identification of alternate paths for each destination node of the network. Due to the cost involved in data transmission, there was need for a higher energy level with higher frequency of nodes in the network. Through incorporation of a probability model, routing decisions were observed by calculation of the probabilistic value of the network, as shown in Eq. (5) [12].

$$G(P) = \begin{cases} 1\,p \leq p_0 \\ 0\,p > p_0 \end{cases} \tag{5}$$

The value 1 denotes a successful connection and 0 indicates an unsuccessful connection. In this every packet is transmitted with the p as probability. The probability-based routing involved the analysis of information related to the availability of spectrum for radio environment for communication. This multi-path optimization approach included fog computing approach for the evaluation of end-to-end user communication to maximize channel performance.

The average path of the WSN communication is represented as in Eq. (6),

$$f(v_i) = \frac{1}{\sigma\sqrt{2\prod}} e^{-(p_i - p_{avg})^2/2\sigma^2}$$

$2\sigma^2$ indicates variance of WSN node communication path and p_{avg} provides mean of data transmission in WSN communication.

The effective path for communication of information in WSN network with MG is estimated using Eq. (7),

$$E(N) = \rho d\lambda$$

In this number of nodes, packets transmitted and other factors are presented.

The proposed FGWHO is presented in Algorithm 1.

Algorithm 1: Proposed FGWHO
Initialize population of whale as Xi (i = 1, 2, ..., n)
Estimates the fitness value of whale through search agents
X=identification of best search agent*
while (t <estimate maximum iterations count)
For every search agent in whale
Update a, A, C, l, and p
if1 (p<0.5)
if2 (|A| < 1)
Update current best position of whale
else if2 (|A|>1)
Select a whale random search agent ($X_{r\,and}$)
Update the best search agent in the whale
end if2
else if1 (p 0.5)
Update best search agent position
end if1
end for
Estimate the best search agent higher than those values
Calculate the\search agent fitness
Update X if*
t=t+1
end while
*return X**

4 Construction of routing

The process of constructing FGWHO is based on various factors. At first, each sensor node (SN) communicates with a cluster head (CH) to transmit data [21]. The data transmission incorporates ID and computes the energy level of nodes as R_{max} within wireless communication links. Based on the estimated energy level, the cluster head and sink node are constructed and information is broadcast to the cluster head. Based on the constructed cluster, the network is classified as inter-cluster network or intra-cluster network. The routing leads to the construction of discrete problems.

The proposed FGWHO included an inter-clustering structure of particle initialization with space dimension D and equal number of CHs. The constructed cluster transmitted data in coordinates; it is denoted as $X_{i,d}$, $1 \le i \le N$ and $1 \le d \le m$, with a defined initial routing value of R_{Ri} with sink node. The random number assigned for the sink node was between the range of 0 and 1, stated as $0 < R_{Ri} \le 1$. Based on the inter-cluster structure, the fitness function was evaluated concerning the fitness quality of the particles. The network lifetime was considered concerning the first CH formation and ends. Hence, there was reduced energy for load balancing in the network CHs. In Fig. 2 flow chart for proposed FGWHO model is presented.

Definition 1 The total energy consumed by CHs within the network is represented as E_{total}. The residual lifetime of the CHs in the network is denoted as Resi_Life Time.

Definition 2: The network residual lifetime is estimated based on the fitness function stated in Eq. (8) as follows:

$$FitnessX = Net\_Lifetime \tag{8}$$

To achieve the desired network lifetime, fitness *X* had to be maximized. The particle with larger fitness X provided a significant solution. In the iteration process, the particle size at different instances of time was updated as X_{ki}, $V_{ki}$and $P_{i\text{-}best}$. The values of X_{ki}, $V_{ki}$and $P_{i\text{-}best}$ were updated using the formula stated below: $X_{ki} \le 0$, where $X_{ki} > 1$ is considered as random number lies between 0 and 0.01.

$X_{ki} > 1$, where $X_{ki} > 1$ is reset as 1.

However, the estimated results were considered as minimal, being either 0 or larger than 1. The estimated value can be stated as $0 < X_{ki} \le 1$. Hence, it is necessary to achieve a particle-based network scenario in the iteration phase of particle P_i and $P_{i\text{-}best}$, which can be updated using Eq. (9), as follows:

$$F_{i-best} = \begin{cases} F_i, FitnessX(F_i) > FitnessX(F_{i-best}) \\ F_{i-best,} FitnessX(F_i) \le FitnessX(F_{i-best}) \end{cases} \tag{9}$$

The G_{best}updated using the Eq. (10) as follows,

$$F_{i-best} = \begin{cases} F_i, FitnessX(F_i) > FitnessX(G_{best}) \\ G_{best,} FitnessX(F_i) \ge FitnessX(G_{best}) \end{cases} \tag{10}$$

The above equation continues to process until the maximal iteration is reached with identification of the best solution G_{best}. The cluster head was based on the consideration of the routing information and of the next hoping in the CH, stated as CH_NextHop(CH_i). Every CH_ican is represented as $1 \le i \le m$. In this, the position of $X_{i,d}$ is denoted as the position of the selected elements in CH_Next(CH_i) It was observed that the values obtained for CH_NextHop(CH_i) and CH_Next(CH_i) were1 each. L denotes the integer calculated between CH_NextHop(CH_i) and CH_Next(CH_i), and is defined in Eq. (11) as follows:

$$1 = \mathrm{ceil}(X_{i,d} \times |\mathrm{CH\_Next(chi)}|) \tag{11}$$

The process involved in overall routing within inter cluster is presented between CH and SN. Based on the network and CH status radii of estimated. According to Definition 2, theResi_LifeTime (CH_i) denotes the network condition. The entire network performance can be estimated using Eqs. (12) and (13), as follows:

$$\mathrm{min\_LifeTime} = \min\{\mathrm{Resi\_LifeTime(chi)} | \forall \mathrm{chi} \ \in \mathrm{CH}\} \tag{12}$$

$$\mathrm{max\_LifeTime} = \max\{\mathrm{Resi\_LifeTime(chi)} | \forall \mathrm{chi} \ \in \mathrm{CH}\} \tag{13}$$

The above equations provide the network maximal and minimal values obtained for the lifetime of the CH within the network. These two variables provide information about the overall network condition concerning CH. The actual communication range E_{actual} of every CH is within these two range, and is given by Eq. (14):

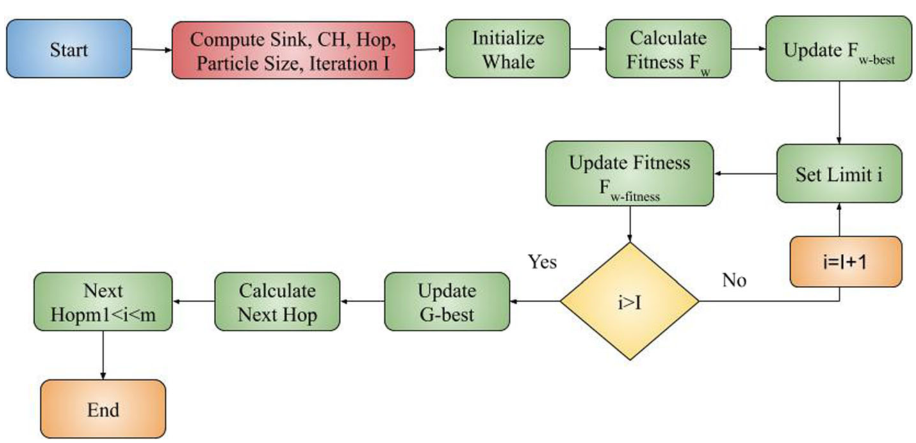


Fig. 2 Flow chart of FGWHO

$$E_{actual}(CH_i) = R_{\max} * \left(1 - \frac{\max\_Lifetime - ResiLifetime(CH_i)}{\max\_Lifetime - \min Lifetime}\right) \tag{14}$$

In a cluster head, the communication range of a network with maximal and minimal values is estimated. The maximal energy range is denoted as R_{max}; it is considered an essential factor for improving network stability and for dynamic and adaptive adjustment in an edge computing network. The actual communication range is relative to the overall network state. The actual and maximal energy estimated for the network can be computed using $E_{actual}(CH_i) \leqslant E_{\max}$.

5 Simulation parameters

The simulation parameters considered for the analysis are presented in this section. The proposed FGWHO optimized the parameters for transmission of data between the sender and receiver with the optimization values. The values considered for analysis are presented in Table 2.

To evaluate the performance of the proposed FGWHO, the simulation was conducted on MATLAB 2019b. The area considered for the analysis to examine the performance of the proposed approach was 500 m × 500 m. The constructed network consisted of 100 CHs and SN count of 1000.

5.1 Comparison technique

The performance of the proposed FGWHO technique was compared with the performances of some existing techniques, such as PSO, ACO [22] and KH [23].

5.2 Performance metrics

5.2.1 Throughput

Throughput is stated as the rate of successful message delivery over communication channels. It is defined in Eq. (15) as follows

$$Throughput = \frac{\text{Successful Reception of Packet}}{\text{Total Time}} \tag{15}$$

5.2.2 Packet Delivery Ratio (PDR)

The network performance metrics are given as the ratio of data packets successfully transmitted to the destination to the total number of packets transmitted from the source. The PDR is given by Eq. (16):

$$PDR = \frac{P_{Received} * 100}{\sum_{i=1}^{n} P_{Generated}} \tag{16}$$

In the above Eq. (16), P_{Received}represents the number of packets received by the sink node, $P_{\text{Generated}}$denotes the packets generated by the source node, and n represents the vehicle count.

5.2.3 Residual energy

The residual energy metric is described as the amount of energy left in the network after sensing, data transmission and data reception. It is defined by Eq. (17):

$$Energy\ Consumed = \sum E_{DT} + E_{DR} + E_{EC} \tag{17}$$

where, E_{DT}—Energy utilized for data transmission.
E_{DR}—Energy consumed for reception of data.
E_{EC}—Energy consumed.

5.3 Discussion

The proposed FGWHO increased the throughput of the network with optimal simulation parameters. The

Table 2 Simulation Setting

Simulation parameters	Simulation value
Number of Sensor Nodes and Cluster Head (CH)	1000, 100
Area Size	500 m × 500 m
Initial Energy for CH	15 J
Initial Energy for Sensor Node	4 J
Maximum coverage area of CH	200 m
Maximum coverage area of sensor node	25 m
Data Size	250 KB
Simulation Software	Network Simulator 2 (NS2)

Fig. 3 Comparison of throughput

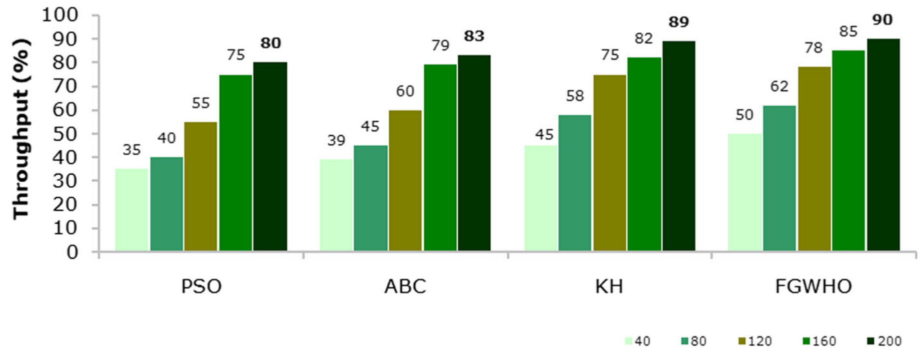


Fig. 4 Comparison of PDR

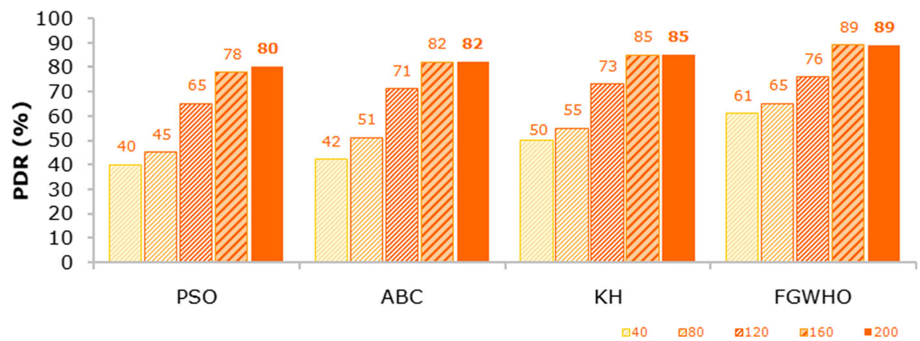
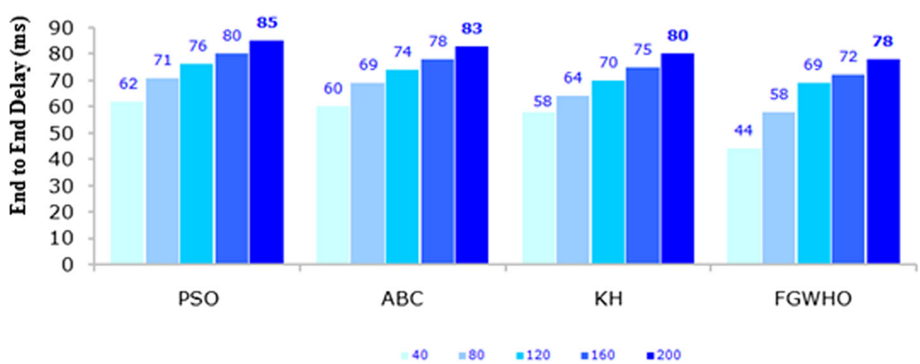


Fig. 5 Comparison of End-end-delay



parameters were estimated based on the consideration of data transmission and reception.

The proposed FGWHO yielded a higher throughput as shown in Fig. 3 value than the existing techniques.

The throughput measured for the proposed FGWHO was significantly higher than those of the other optimization techniques, such as PSO, ABC and KH. Successful reception of data packets for a specified period was observed for the proposed FGWHO. The comparative analysis of throughput with existing technique stated that the proposed FGWHO exhibits $\sim$ 7% to 10% improvement rather than other existing techniques. In Fig. 4 shows comparative analysis of PDR measured for proposed FGWHO is illustrated.

This comparison shows that the proposed approach exhibited improved performance. The proposed FGWHO PDR was significantly higher than those of the existing optimization techniques. Similar to throughput the developed model exhibits higher PDR rather than existing techniques such as PSO, ABC and KH. The analysis exhibited that proposed FGWHO exhibits $\sim$ 10%, $\sim$ 9% and $\sim$ 7% improved performance than PSO, ABC and KH respectively.

The above Fig. 5 shows end-end delay comparison of proposed and existing technique.

The above Fig. 6 shows packet transmission coverage area comparison of proposed and existing techniques.

Residual energy represents the amount of energy left in the network after data transmission. Figure 7 comparative analysis of proposed FGWHO model with existing optimization technique is presented.

The comparative analysis showed that the proposed FGWHO exhibited significantly higher residual energy

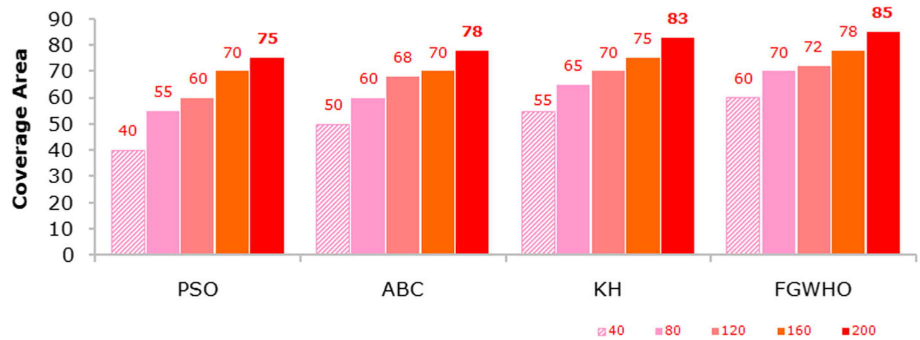


Fig. 6 Comparison of packet transmission coverage area

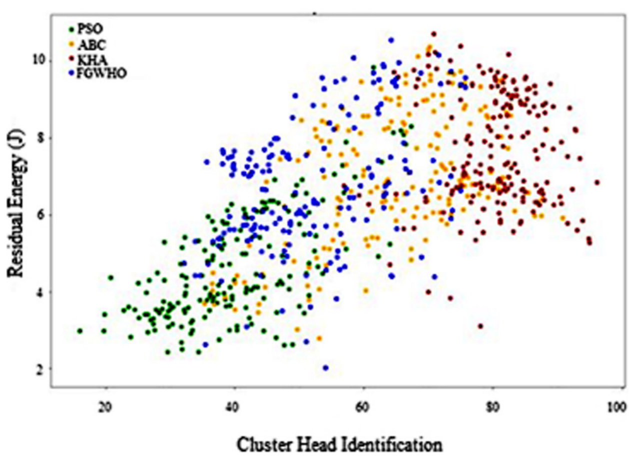


Fig. 7 Comparison of residual energy

than the other existing optimization techniques (PSO, ABC and KH).

6 Conclusion

In this paper, we have proposed an FGWHO algorithm incorporating whale optimization and a fog computing network. The proposed approach focused on improving the lifetime of the network through optimal routing of a grid-connected system to prevent malfunctioning. The selected CHs concentrated on improving the communication range of the network for optimal load in the network. Based on WHO, the network was constructed to estimate energy, communication and the distance between grid-connected networks. The proposed FGWHO algorithm exhibited improved network performance in terms of throughput, PDR and residual energy. In future, grid-connected renewable systems can be designed and optimized for the estimation of effective data transmission between sensor nodes.

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