

Energy Aware WSN Transmission and Network Lifetime Improvement using Particle Swarm based Distance Error Optimization

Prof. Manoj Challa

Research Scholar, S.V.U College of Engineering, Tirupati, India.

Dr. M. Damodar Reddy

*Professor, Department of Electrical and Electronics Engineering,
S.V.U College of Engineering, Tirupati, India*

Dr. P. Venkata Subba Reddy

*Professor, Department of Computer Science and Engineering,
S.V.U College of Engineering, Tirupati, India.*

Abstract

Recently demand of wireless communication has increased rapidly. In wireless communication system, wireless sensor networks have gained huge attraction from researchers due to its significant nature of information gathering and quick deployment etc. WSN suffer from various challenges such as security, complexity and energy consumption etc. but energy consumption is considered most challenging task because it can affect the network performance due to less network lifetime because these nodes or sensors are powered by battery which has limited source. Hence, energy consumption becomes a primary task for any WSN to maintain the network lifetime for desired information gathering from the deployed region. In this work, we have addressed this issue of energy consumption in WSN and developed a new approach by taking the advantage of bio-inspired and artificial intelligence algorithms. During data transmission or reception, distance error between node/range of node (whether the receiving node or transmitting nodes are in the range of each other or not) can cause packet drop and can affect the routing by raising rerouting issue. This issue is addressed by using particle swarm optimization scheme which uses iterative updating process and provides optimal coordinate points of the other node for reliable communication. Furthermore, energy consumption of the node also considered where various parameters such as distance from sink, number of agents and neighbors are taken for neural network training and finally a prediction is obtained which helps to estimate the status of node whether it can be carried forward for next iteration or not. These predictions are made based on the consumed energy and required energy for data transmission by the node. An extensive simulation and comparative study is presented which shows that proposed approach achieves better performance when compared with state-of-art techniques of energy aware routing in wireless sensor networks.

Keywords: Wireless sensor networks (WSN), Artificial intelligence and neural network

INTRODUCTION

In the recent era, demand of communication has increased drastically with the help of wired and wireless communication systems. Wireless communication systems are in high demand due to their significant nature of communication such as mobility, portability etc. In this field of wireless communication, wireless sensor network is considered as a revolutionary technique which can improve the communication performance. Recent technological advancements lead to manufacturing of ultra-small, battery operated, low-cost and multi-functionality nodes [1]. These ultra-small sensors are considered as sensor nodes which are used for surrounding information aggregation and reveals the information of phenomena occurring in the range of sensor node deployment. Combination of several sensor node forms wireless sensor network. In order to formulate network, these sensor nodes either can be placed randomly or can be deployed over a defined geographical area, connected through wireless communication links. In wireless sensor network, a base station node also plays an important role where each node can communicate with the base station for information exchange. Wireless sensor network contains small sensor nodes which have several capabilities such as data sensing, computation and communication etc. [2]. During communication, each sensor node collects the data from the deployed area and performs routing to transmit the information to the base station [3]. This data transmission occurs in the form of multi-hop communication, where data transmission takes place from node to node towards the base station. Wireless sensor networks are adopted in various application i.e. military, industrial and civil applications. In military field, it includes various applications such as intrusion detection, battlefield surveillance, target field and imaging. However, WSN are now being used in many civilian application areas too, including environment and habitat monitoring, health applications, home automation and traffic control.

In wireless sensor networks, sensor nodes have some limitation constraints such as power consumption, memory utilization and node lifetime. However, wireless sensor nodes are powered by battery which leads to network life time issues

for continuous communications. Moreover, topology of wireless sensor network is unpredictable because at any point of time, a new node can be added or removed which causes uncertainty in the network. Generally, battery capacity, bandwidth utilization and power consumption are challenging issues in any WSN. Hence, network life time issue can be catered by optimizing power consumption and network energy utilization during communication. In order to deal with these issues, Anisi et al. [4] discussed about the issues and challenges in WSN. Energy consumption for communication is a crucial task which can degrade the performance of network. Recently various approaches have been presented for efficient routing protocol development in the WSN. However, routing based energy conservation is still considered as a challenging task for researchers.

WSN are known because of their continuous data gathering nature. During this process, interference can degrade the communication performance. To cater this issue, clustering is considered a promising technique for WSN performance improvement [5]. Several clustering schemes have been presented. Clustering & routing schemes have been adopted widely in WSN for performance improvement. Routing schemes can be categorized as follows:

- Network based routing
- Location based routing
- Flat based routing
- Hierarchal based routing
- Protocol based routing
- Negotiation based routing
- Multipath based routing
- Query based routing
- QoS based routing

In this field of efficient routing in wireless sensor networks, soft computing and machine learning techniques also shown significant performance improvement. In order to perform efficient routing, various soft computing techniques have been presented by researchers. These techniques consider multiple aspects of network performance such as power consumption, delay etc. Some of the well-known techniques are Evolutionary Algorithms (EA), Swarm Intelligence (SI), Reinforcement Learning (RL), Fuzzy Logic (FL), Neural Networks (NN) and Artificial Immune System (AIS). These techniques have been used widely in this field of WSN. Recently, in [6], evolutionary computation scheme is presented for WSN routing. Conventional technique such as LEACH also provide better lifetime of the network but computational complexity and stability issues need to be eliminated to obtain the desired life time performance. Bio-inspired techniques can be utilized for energy efficient communication in WSN. Furthermore, neural network based technique also can be implemented for efficient routing in WSN [7].

Issues and challenges

There are various issues present in wireless sensor network communication. Main issues are: energy consumption during communication, MAC layer issues, Quality of Service, Data security, network architecture, network deployment, data storage and localization etc. However, huge amount of work has been carried out in this field of WSN. Still, conventional approaches suffer from various performance issues in WSN such as security, energy consumption and Quality of Service etc. In this work, we mainly focus on the energy optimized routing scheme for wireless sensor networks resulting in better quality of service.

Contribution of this work:

Previous section described the applications of WSN, issues and challenges in WSN. Now-a-days, energy consumption optimization in WSN is a challenging task for researchers. In order to improve the network performance, we develop energy efficient routing approach using artificial intelligence techniques in WSN. According to the proposed approach, first of all a wireless sensor network is formulated, in next phase we formulate energy modeling for WSN, next phase contains problem formulation and finally, we present neural network based solution for energy efficient routing for packet delivery in WSN.

Organization

Rest of the manuscript is organized as follows: section II describes literature review of recent studies in WSN field for energy consumption minimization. Section III presents proposed solution using artificial intelligence scheme, section IV describes experimental studies and finally manuscript is ended with concluding remarks.

LITERATURE SURVEY

This section presents a brief study about recent studies in the field of WSN performance enhancement. As discussed before, several challenging issues are present in WSN which degrade the communication performance. Performance of any wireless sensor network depends on the energy consumption, since sensor nodes are battery powered which raise the issue of network lifetime. Hence, the overall performance can be enhanced by optimizing energy consumption in the network with the help of routing techniques. For any real-time wireless communication system, quality of service is considered as important aspect. There are various challenges present to meet the quality of service requirement for the users. Networking protocols play important role to satisfying the QoS requirement. In various network applications, network traffic is a mixture of delay sensitive and delay tolerant. Hence, QoS provisioning becomes an important task for network performance improvement. Othman et al. [8] discussed about QoS issues and developed energy efficient and QoS aware multipath routing protocol for network life-time maximization, delay reduction and improvement in end-

to-end throughput. This approach developed a new approach of next hop prediction where residual energy, buffer size and SNR are used for next hop prediction during path construction phase.

Mao et al. [9] presented a study about wireless sensor networks. Several routing protocols have been introduced but opportunistic routing can significantly improve the performance of the network in terms of throughput. This methodology formulates a forwarder list where packets participate which are closer to the destination. Furthermore, each packet of forwarder list are prioritized in terms of higher and lower priorities, at this stage, of packet is forwarded from higher priority to lower priority order node then it is discarded. This approach can improve the network performance but selection of prioritize forwarder can optimize the performance by minimizing energy consumption. Similar to [9], Eu et al. [10] also presented energy consumption modeling for wireless sensor networks. Conventional techniques are basically dependent on the sleep-and-wakeup process which cannot be considered as significant approach for energy optimization model for WSN. A novel approach is developed in this work using opportunistic routing protocol for multi-hop wireless sensor networks. Conventional approaches such as ExOR or MORE, EHOR considers energy constraints because nodes have to shut down to recharge once their energy are depleted.

Furthermore, since the rate of charging is dependent on environmental factors, the exact identities of nodes that are awake cannot be determined in advance. Therefore, choosing an optimal forwarder is another challenge in EHOR. Zhang et al. [11] analyzed performance issues in wireless sensor networks and found that energy consumption during data transmission reduces network lifetime which fails to obtain desired communication performance. Hence, authors presented energy-balanced routing method based on the forward-aware factor described in this work. In order to select the next-hop, link weight awareness and forward energy density parameters are considered for analysis. Moreover, spontaneous reconstruction approach is implemented for topology design. As discussed before, wireless sensor networks suffer from energy-consumption issues. Existing techniques in WSN uses energy-aware routing for packet forwarding to minimize the energy consumption. This process of data transmission may lead to random or unbalanced energy distribution in nodes which can partition the network in different sections based on the energy. To overcome this issue, Ren et al. [12] developed a novel approach known as energy-balanced routing protocol with the help of energy density and residual energy etc. This technique focuses on packet forwarding to the sink node through dense energy area which consumes lower residual energy. During transmission, looping occurs which consumes more energy for each transmission. This work addresses this this issue and develop a loop elimination process.

For performance enhancement of WSN, geographic routing is also adopted widely. According to this routing mechanism node location parameters are considered as main parameter for packet forwarding. This approach for routing mainly depends on the resource-constrained sensor networks.

However, conventional sensor networks causes network overhead due to route establishment, route maintenance, memory requirement indications and higher demand of scalability in the distributed network applications. Along with this issue, accurate position information of each node and its neighboring node is also required. In wireless sensor network where network topology is changing slowly, neighboring information maintenance can improvise the performance of the network because maintained information is reusable in nature which reduces computation cost. However, recent wireless sensor network scenarios are dynamic in nature due node mobility, node sleeping [13], faulty node, or link failure etc. [14]. Zhang et al. [15] discussed about the geographical routing technique in WSN. In order to mitigate the issues related to dynamic WSN, a novel online routing approach is presented in this work which is called as called Energy-efficient Beaconless Geographic Routing (EBGR). The main contribution of this work is to provide loop-free, stateless and sensor-to-sink routing with lower communication overhead without considering any prior knowledge of neighboring node. First of all, next-hop relay position is computed and each forwarder node selects the next-hop position using RTS/CTS handshaking mechanism.

Wireless sensor networks face several challenges for providing significant communication, limited energy resource is considered a crucial part which can affect the performance of WSN because sensor nodes are battery operated. To overcome this issues, clustering techniques are used widely for sensor energy level conservation [16]. In WSN clustering approach, cluster head formulation takes place which operates as controller for managing the wireless network i.e. information exchange etc. [17]. According to Wei et al. [18], during heavy traffic loads, hot spots are used as locations in WSN. In any network, quick depletion of energy may lead to the degraded performance of network. Similar scenario occurs on cluster head based networks where huge amount of information is gathered and relayed to other nodes in the network. Conventional approaches contains static cluster head where distance from the communicating node causes energy consumption issue hence development of rotated cluster head or dynamic cluster head selection can provide efficient performance to the network. Authors developed energy efficient clustering for suitable cluster head selection based on the hop distance to the sink resulting maximization of node lifetime. In this field of WSN communication, Karaboga et al. [19] discussed artificial intelligence approach for energy aware communication. Various studies shown that clustering can improve the energy efficient performance of the network. For further enhancement in this, artificial intelligence is utilized along with bee colony optimization. Based on optimization techniques, Kuila et al. [20] introduced particle swarm optimization technique for optimizing the performance of WSN. Authors presented Linear/Non-linear problem formulation with particle swarm optimization. In this work, WSN routing is presented with the PSO encoding using multi-objective fitness function. Bagci et al. [21] developed fuzzy logic based model for energy aware communication in wireless sensor networks. This work mainly focuses on cluster head selection where energy-aware unequal algorithm is applied for clustering. This section describes various

algorithms for energy aware transmission in wireless communication in WSN. State-of-art techniques shown that clustering and routing techniques can improve the performance of wireless sensor networks. However, sensor nodes are power by battery which has limited power supply. Still, various challenging issues are present in energy-aware techniques such as computational complexity, data delivery delay and quality of service (QoS) etc. Hence there is a need to develop an improved approach for routing in wireless sensor networks.

PROPOSED MODEL

This section presents the proposed approach for efficient routing in wireless sensor networks. Proposed development is categorized into three main categories as: wireless sensor network formulation, sensor node energy modelling and neural network based optimization model for solving the problem.

a. Network Model formulation

In this subsection we initialize with the basic considerations and network environment where sensor nodes are being operated. However, these assumptions can be varied according to the network modeling conditions. It is also considered that each node is communicating in homogenous wireless medium. Wireless sensor network model is presented in the form of undirected graph as $G = (V, E)$ where V denotes the set of all sensor nodes along with base station, network edges or links are denoted by E , in this model neighboring nodes are denoted by u and communication between nodes is in commutative nature i.e. node v can receive message from node u and similarly, u also can receive message from v . These transmission are considered as isotropic and are omnidirectional which can reach to all neighboring nodes. Distance between nodes u and v is denoted by d as $d(u, v)$, hence edges can be expressed as:

$$E = \{(u, v) | u, v \in V \text{ and } d(u, v) \leq R$$

and u, v are optional}

Constructed graph is similar to the unit graph where each node's transmission ranges are equal. Here, neighborhood of node u is denoted as:

$$N(u) = \{v | (u, v) \in E\}$$

All these nodes are homogenous and carry some properties which include unique identity which can be considered as address of the node during transmission. Each of the node (i) contains fixed and finite energy denoted as (P_i) and each node is provided fixed radius of communication as R . Figure 1 shows a general distribution of sensor nodes in the network where outer circle shows the WSN deployment area and communication range of nodes is

denoted by two inner circles. During communication process, if node failure occurs then vertices and edges of the network also change which may lead to variation in possible communication among pairs of node. In any given network, nodes play different type of roles such as routing, data sensing, ideal mode operation and both sensing & routing. Based on these operations cost of each operation is associated. Sensing operation is assigned with a cost parameter as c_s , message transmission (which contain the information related to the sensory computation) cost is denoted by c_t , message reception cost is denoted by c_r and data aggregation cost is denoted by c_a .

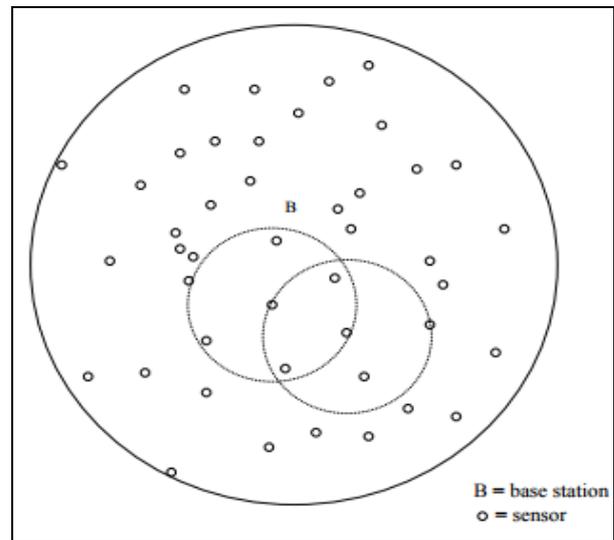


Figure 1. Wireless network model and sensor node distribution

In order to estimate the energy consumption, a radio transceiver model is applied in this work. At this phase, packet transmission by any sending node to other neighboring receiver node, the required amount of energy can be calculated by adopting [22] such as:

$$e = e_t + n.e_r + (N - n)e_r^h$$

Where e_t denotes the amount of energy required for data transmission, e_r denotes the amount of energy required for data reception, receiving node identity is denoted by n and total numbers of neighbor nodes in the range are denoted by N . Further e_t and e_r can be computed as follows:

$$e_t(d, k) = 8k * (e_{elec} + e_{amp} * d^p)$$

$$e_r(k) = e_{elect} * 8k$$

According to [22], for distance d and k byte message we have considered some constant parameters as

$$e_{elect} = 70 \text{ nJ/bit} \quad , \quad e_{amp} = 120 \text{ pJ/bit/m}^2, \\ d = 50\text{m} \text{ and } \rho = 4.$$

During data transmission or exchange in WSN, link cost between two nodes can be estimated by computing the energy spent by these nodes to transmit and receive the data packets. Therefore, in order to establish connectivity and coverage aware connection between nodes, routing metric can be formulated which helps to establish the connection between the sensors. This routing metric can be defined as follows:

$$R_{metric} = \left\langle \frac{E_i^D}{E_t(S_i, S_j) + E_r(S_i, S_j)} \right\rangle$$

E_i^D denotes a measurement of energy which is associated with packet delivery ratio where packet is originated from source node and delivered successfully at the destination, $E_t(S_i, S_j)$ denotes transmission energy where data is transmitted from source node to destination node and $E_r(S_i, S_j)$ denotes reception energy consumed during packet reception.

After this complete modeling, a problem related to this can be formulated by considering network model as depicted in figure 1. In this process, the overlapping of the network or thickness t_i of inner circles are responsible for energy consumption therefore this can be minimized and optimized. In order to address this issue, a problem formulation model is presented. Let us consider that n_i is the number of nodes in the inner circle, for this cumulative parameters can be defined as:

$$T_i = \sum_{j=1}^i t_j, \quad \mathcal{N}_i = \sum_{j=1}^i n_j$$

Total number of dispersed sensors (n_i) in the area can be computed as $n_i = \mathcal{N} \frac{T_i^2}{R^2}$. During each round of communication, packet is transmitted to the data sink. In this process, some energy is required for data transmission and reception. Receiving and transmitting packets should be distributed evenly to achieve efficient communication without generating overhead on any of the node. This even distribution helps to reduce the network overhead, as follows. Let us consider that transmission distance of a sensor node $x_i(r)$ is in the range of inner circle at a distance r from sink node. From figure 1, $D_{i-1} \leq r \leq D_i$.

According to the energy model, sensor node i at r distance from the sink will consume k_i units of energy for packet reception and $k_i(1 + \mu x_i(r)^\alpha)$ for forwarding the packets. Based on this, the energy consumption of the sensor can be expressed as:

$$e_i(r) = k_i(1 + \mu x_i(r)^\alpha) + k_i(2 + \mu x_i(r)^\alpha)$$

In this work, a general signal propagation mode is adopted where signal power attenuation is proportional to d^α , α is considered as 2 which used for small distance free space propagation. For multi-path fading consideration, α values are high. In simplified way, \mathcal{N} number of sensors are deployed randomly in an area \mathcal{A} . Each sensor node contains a transmission range R and initial energy E_0 . It is assumed that for 1-hop communication each node consumes E_c^i . In order to realize this problem for WSN performance, following constraints are considered such as :

Energy consumption as $\sum E_c^i \leq E_0$ for $i = 1, 2, 3, \dots, \mathcal{N}$

Maximum lifetime constraint as $E_c^i \leq P_{max}$

Optimal solution of these two constraints can lead to improved performance of WSN in terms of energy consumption, maximum network lifetime and efficient packet delivery. In order to obtain the optimized distance between inner circles and efficient routing, we adopt PSO (Particle Swarm Optimization) approach as discussed in next subsection.

b. Overview of particle swarm optimization

Particle swarm optimization technique is a well-known bio-inspired optimization technique which is adopted widely for obtaining optimal solution solutions. The working process of this technique is inspired from natural life that animals, birds etc. follow a group and travel without any collision because of their self-adjustment nature of position and velocity based on the group information. To obtain the desired performance of this approach various steps need to be performed as given in figure 2.

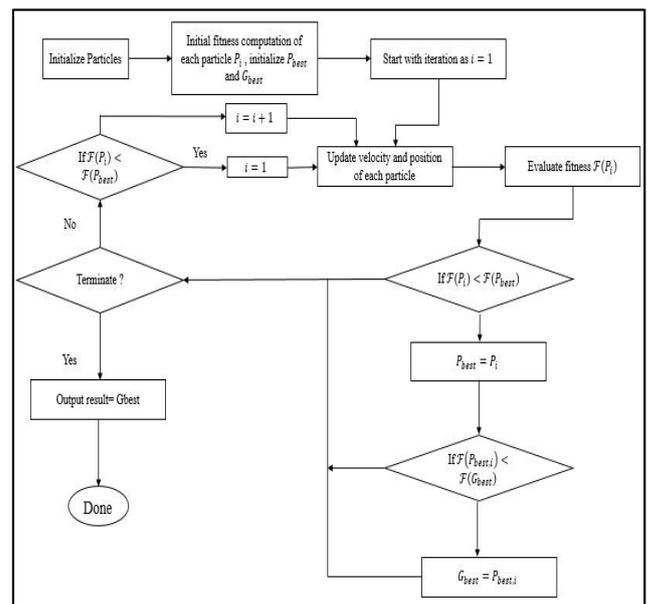


Figure 2. PSO algorithm flow chart

PSO contains a predefined size of swarms (N_p) particles. Each particle is capable to provide the solution for any multidimensional optimization problem. Let a particle $P_i, 1 \leq i \leq N_p$ has initial positions as $1 \leq d \leq D$ with velocity $V_{i,d}$. Initial population can be denoted as:

$$P_i = [X_{i,1}, X_{i,2}, X_{i,3}, \dots, X_{i,D}]$$

In this technique, fitness function is an important parameter which helps to analyze the quality of obtained solution. For obtaining the optimal solution, own best is denoted by P_i which is estimated using personal best (P_{best}) and global best (G_{best}) solutions which is used for updating the velocity and position of the particles. Position, velocity and dimension updating process can be expressed as:

$$V_{i,d}(t) = w \times V_{i,d}(t-1) + c_1 \times r_1 \times (XP_{best_{i,d}} - X_{i,d}(t-1)) + r_2 \times c_2 \times (XG_{best_{i,d}} - X_{i,d}(t-1))$$

Similarly, position update can be expressed as:

$$X_{i,d}(t) = X_{i,d}(t-1) + V_{i,d}(d)$$

Where inertial weight is denoted by w , c_1 and c_2 are two non-negative constant known as acceleration factor, r_1 and r_2 are uniformly distributed numbers ranging from 0 to 1. This process of velocity and position updating is performed iteratively until G_{best} is achieved or maximum number of iteration achieved.

c. PSO for WSN

In this work, we have applied particle swarm optimization process for WSN routing. Particles are represented such a way that it contains information related to route from each cluster head to the base station. Particle data dimension is considered equal to the total number of gateways in network. Each component of this process is initialized randomly with a uniformly distributed number. Gateway and node positions are mapped towards base station resulting in formulation of relay for data transmission.

In next stage of PSO, a fitness function is computed for performance evaluation which is used for updating the global and best positions of the particles. The desired performance of the WSN can be obtained by achieving two main objectives which are: (a) minimization of distance between two communicating nodes (b) minimization of number of hops used for communication by gateways. This can be obtained by applying fitness function computation. To do this, weighted sum approach is considered for analysis which can provide solution for multi-objective optimization problem. Fitness function can be expressed as:

$$F = W_1 \times Max_{Dist} + W_2 \times Max_{Hops}$$

During this process, various computations take place which may lead to the new position in negative or greater than the range which misleads the position parameters. In this scenario, particle must satisfy the predefined range as $(0,1]$. Further adjustments can be made such as if newly computed value is zero or negative then it can be replaced by the randomly generated value tending to zero and if value is greater than one then it can be replaced by 1. In next stage, each particle P_i is examined by applying fitness function. At this phase, personal best (P_{best}) can be replaced by its own value only if the current value of fitness is better than P_{best_i} value. This process can be expressed as:

$$P_{best_i} = \begin{cases} P_i & \text{if } (fit(P_i) < fit(P_{best_i})) \\ P_{best_i} & \text{otherwise} \end{cases}$$

$$G_{best} = \begin{cases} P_i & \text{if } (fit(P_i) < fit(G_{best})) \\ G_{best} & \text{otherwise} \end{cases}$$

A brief process of particle swarm based routing is presented in algorithm 1

<p>Input: (1) Set of communicating nodes and cluster heads, (2) total number of hop count (3) swarm size with the constant parameters</p> <p>Output: final route with less number of hop count and less energy consumption</p>
<p>Step 1: Initiate random particles P_i</p> <p>Step 2: for $i= 1: N_p$ do Fitness function computation $P_{best_i} = P_i$ end</p> <p>Step 3: global best fitness computation i.e. $G_{best} = \{P_{best_k} F(P_{best_k}) = \min(F(P_{best_1}), \forall_i, 1 \leq i \leq N_p)$</p> <p>Step 4: do while (! Terminate) For $i= 1: N_p$ do Velocity and position update of the particle Fitness function computation If $F(P_i) < F(P_{best_i})$ then $P_{best_i} = P_i$ Else $(P_{best_i}) < F(G_{best_i})$ then End End</p> <p>Step 5: Compute next hop position using global best solution.</p>

This complete process of particle swarm optimization helps us to achieve an efficient routing in WSN. The impact of this technique on network performance is presented in the results section. As of now, we have developed a routing mechanism for WSN where minimum number of hops and distance parameters are optimized. Furthermore, the performance of network can be improved by taking the advantage of neural network based artificial intelligence technique. According to this stage, we utilize neural network to predict the energy level of the node in upcoming iteration so that the node can be kept as a participating node in the minimum hop count path or else it can be discarded. In the case of discarding, PSO routing need to be reinitialized to achieve the new routing path for WSN communication.

d. Neural Network based node energy estimation

Neural network is known as an artificial intelligence process whose working is similar to the human brain. This approach uses human brain interface and can establish relationship between complicated inputs and desired output variables by learning the pattern of input data. In this work, we have used multilayer perceptron based neural network which contains input layer, non-linear hidden layer and output layer. A generic model of MLP neural network is presented in figure 3.

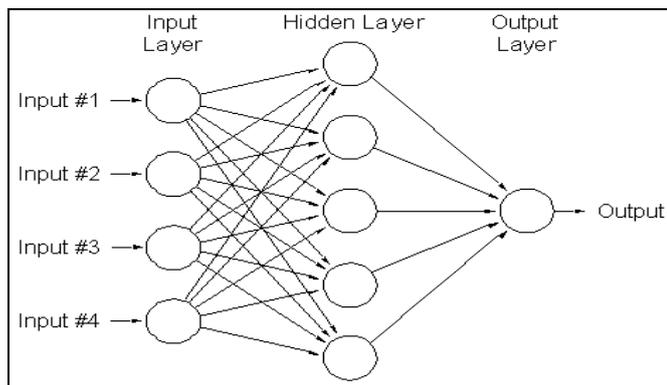


Figure 3. MLP neural network model

In this process, number of neurons as input units, hidden layer and output layers are denoted by n , h and o respectively, the output of NN can be computed as:

$$p(w_k|X) \approx y_k = f \left\{ \sum_{j=1}^p w_{jk} f \left(\sum_{i=1}^n v_{ij} x_i \right) \right\} \text{ for } k = 1, 2, \dots, o$$

Where f denotes activation function, w_{jk} denotes hidden-output weights and v_{ij} denotes input to hidden weights. Furthermore, to predict the energy level of the node, some essential attributes are defined as input to the neural network. These attributes include: sensor-sink distance, sensor distance from nearest inner circle, total neighbors and sensor agents which are used initially for data routing.

In next phase, base-station node receives the information of node in terms of node positions and neighboring position which helps to determine the other attribute values required for neural network learning. Based on these values of each node, neural network is trained and used for prediction the status of nodes in upcoming iterations. A sample model of neural network implementation is depicted in figure 4.

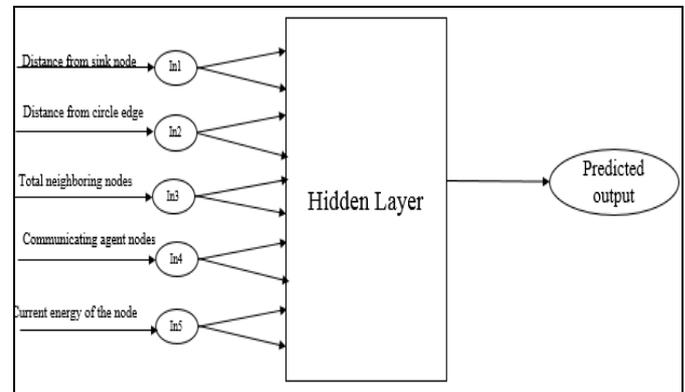


Figure 4. Neural Network model for WSN

In this figure, all attributes are given to each layer where weight of each pattern will be computed and processed through hidden layer. Hidden layer uses some predictive computational analysis for predicting the next hop energy level and stores which can be compared in next iterations for delay reduced and power conserving transmission in WSN.

EXPERIMENTAL RESULTS AND DISCUSSION

Complete experimental study and performance of proposed model is described in this section. In order to evaluate the performance of proposed approach, MATLAB 2013b simulation tool is used along with C++ programming language. Complete simulation parameters are described in table 1.

Table 1. Simulation parameters

Parameter	Value
Network Area	500 × 500 m ²
Total number of sensor nodes	100
Initial energy	0.5 J
E_{elec}	50 nJ/bit
E_{amp}	0.0013 pJ/bit/m ⁴
Packet Size	4000 bits
Message size	200 bits

Similarly, particle swarm optimization and neural network parameters are also used as mentioned in table 2.

Table 2. PSO and neural network parameters

Parameter	Values
Initial population	100
PSO constant C_1	1.49
PSO constant C_2	1.49
Weight constant	0.79
Max speed	0.5
Minimum Speed	0.5
Hidden layer	5
Iteration	1000
Weight sum vector W1	0.2
Wight sum vector W2	0.8

An extensive study is carried out for analyzing the performance of proposed approach. For simulation study, we have considered two different experimental studies denoted as WSN#1 and WSN#2. These networks are provided a sensing area as mentioned in table 1. For first scenario WSN#1, base station positions are considered at coordinates (500,250) and for case 2, WSN#2 position of base stations are considered at (250,250). For PSO approach, initially 100 particles are considered for simulation. However, these parameters can be varied according to the requirement.

First of all, we have evaluated the performance of proposed model in terms of alive nodes where varied number of iterations are considered, 1000 number of iteration were considered as maximum number of iteration. In order to show the robustness of proposed mode we have compared the performance of proposed approach with state-of-art algorithm in terms of number of alive nodes.

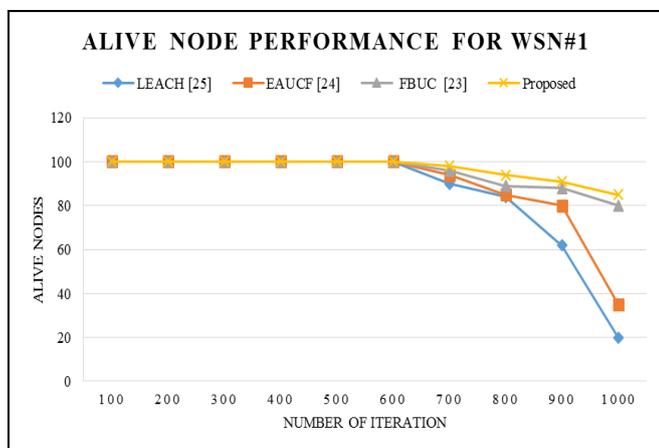


Figure 5. Alive node performance analysis

Figure 5 shows a comparative study in terms of total alive nodes. This study shows that proposed approach achieves better performance when compared with recent existing WSN routing techniques. According to this analysis, it was found that average number of alive nodes were 85.6, 89.4, 95.3 and 96.8 in LEACH, EAUCF, FBUC and proposed approach respectively. This performance analysis shows experimental performance for WSN#1 scenario.

Similarly, we evaluate the performance of total number of alive nodes for wireless sensor network case 2 where base station is placed in the center of the region. Comparative study is presented in figure 6 which shows that proposed approach outperforms when compared with existing models.

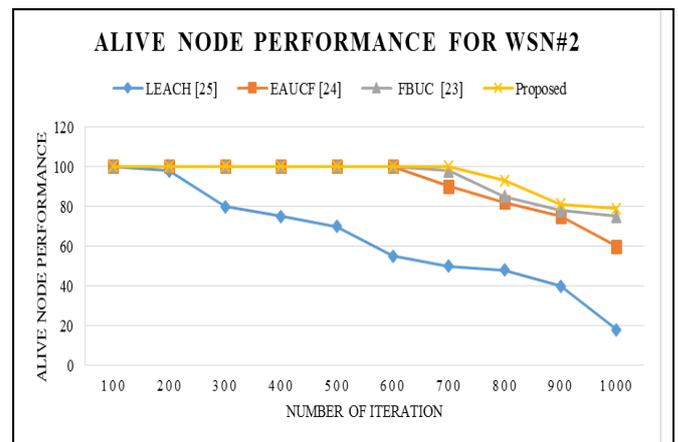


Figure 6. Node alive performance for WSN#2

In next phase of experiment, we perform a comparative analysis in terms of network lifetime for varied number of nodes. This lifetime is analyzed in terms of network rounds. Figure 7 shows experimental performance for WSN#1 and figure 8 shows a comparative performance for WSN#2.

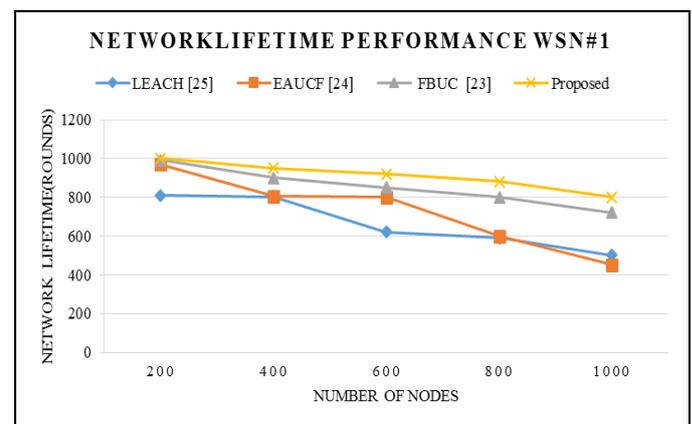


Figure 7. Network lifetime performance for WSN#1

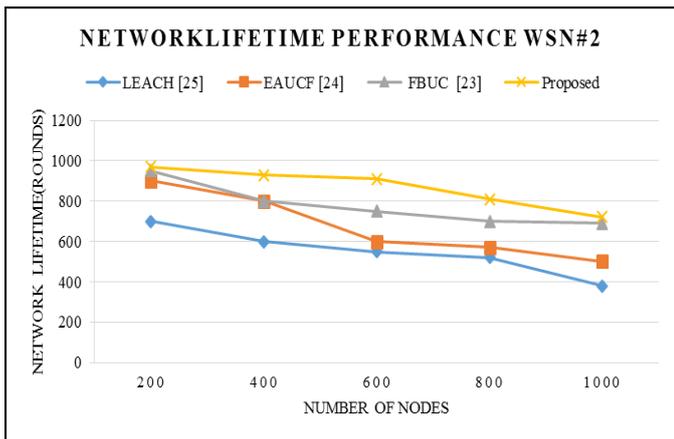


Figure 8. Network lifetime performance for WSN#2

In test case 1, for network lifetime performance, proposed approach shows better performance. According to this analysis, 664, 725, 852 and 910 rounds average lifetime is obtained for LEACH, EAUCF, FBUC and proposed approach respectively whereas for second test case 550, 674, 778 and 868 number of average round network lifetime is obtained for the above mentioned algorithms respectively. Finally, we present residual energy comparison analysis for both test cases by varying the number of rounds. This analysis is presented in figure 9 & 10 for WSN#1 and WSN#2 respectively.

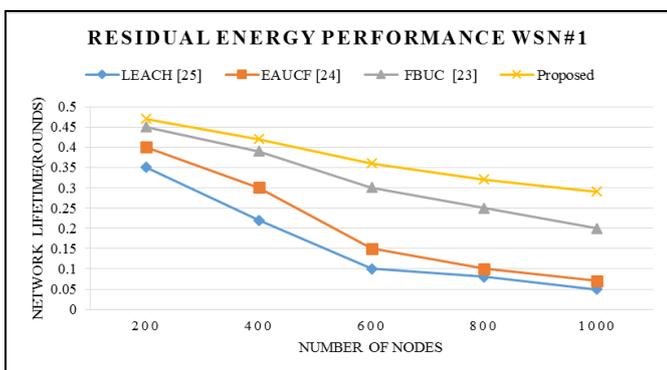


Figure 9. Residual energy performance for WSN#1

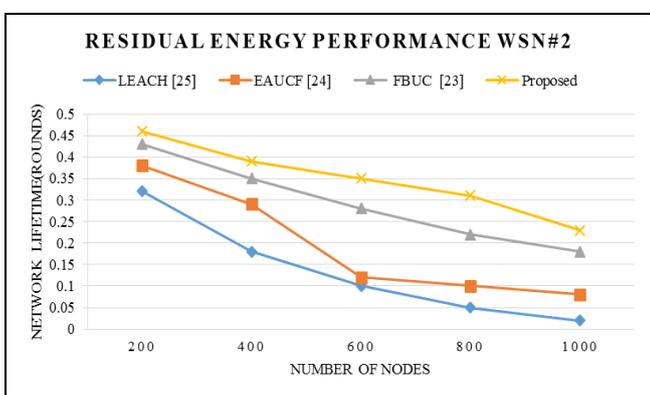


Figure 10. Residual energy performance for WSN#2

CONCLUSION

An extensive study is carried out in this work regard wireless sensor networks and it was analyzed that energy consumption is still remains a challenging task which may lead to performance degradation of the network due to less network lifetime. To overcome this issue, in this work we have presented bio-inspired and artificial intelligence based approach for energy efficient routing model for WSN applications. In order to carry out this research, particle swarm optimization scheme is developed first to model the routing and distance error optimization between nodes. In next phase of work, neural network process is implemented for predicting the node status whether that particular node can be carried forward for further process or need to be discarded from the routing path. This estimation is performed based on the required energy of data transmission and reception during communication. MATLAB simulations are carried out to evaluate the performance of proposed approach. Moreover a comparative study is also presented by considering recent well-known routing techniques where it can be concluded that proposed approach outperforms when compared with state of art model of routing.

REFERENCES

- [1] F. A. Aoudia; M. Gautier; O. Berder, "Distributed Computation of Fair Packet Rates in Energy Harvesting Wireless Sensor Networks," in *IEEE Wireless Communications Letters*, vol. PP, no.99, pp.1-1, 11 July 2017.
- [2] Fei, Zesong, et al. "A Survey of Multi-Objective Optimization in Wireless Sensor Networks: Metrics, Algorithms, and Open Problems." *IEEE Communications Surveys & Tutorials* 19.1 (2017): 550-586.
- [3] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, (2002), "A Survey on Sensor Network", *IEEE Communication Magazine*, vol. 40, no.8, pp. 102 – 116.
- [4] Anisi, Mohammad Hossein, et al. "Energy harvesting and battery power based routing in wireless sensor networks." *Wireless Networks* 23.1 (2017): 249-266.
- [5] Fujii, Shohei, et al. "Optimal cluster head selection and rotation of cognitive wireless sensor networks for simultaneous data gathering." *Information Networking (ICOIN), 2017 International Conference on.* IEEE, 2017.
- [6] Bara'a, A. Attea, and Enan A. Khalil. "A new evolutionary based routing protocol for clustered heterogeneous wireless sensor networks." *Applied Soft Computing* 12.7 (2012): 1950-1957.
- [7] Nehra, Neeraj Kumar, Manoj Kumar, and R. B. Patel. "Neural Network based energy efficient clustering and routing in wireless sensor networks." *Networks and Communications, 2009. NETCOM'09. First International Conference on.* IEEE, 2009.

- [8] Ben-Othman, Jalel, and Bashir Yahya. "Energy efficient and QoS based routing protocol for wireless sensor networks." *Journal of Parallel and Distributed Computing* 70.8 (2010): 849-857.
- [9] Mao, Xufei, et al. "Energy-efficient opportunistic routing in wireless sensor networks." *IEEE transactions on parallel and distributed systems* 22.11 (2011): 1934-1942.
- [10] Eu, Zhi Ang, Hwee-Pink Tan, and Winston KG Seah. "Opportunistic routing in wireless sensor networks powered by ambient energy harvesting." *Computer Networks* 54.17 (2010): 2943-2966.
- [11] Zhang, Degan, et al. "An energy-balanced routing method based on forward-aware factor for wireless sensor networks." *IEEE transactions on industrial informatics* 10.1 (2014): 766-773.
- [12] Ren, Fengyuan, et al. "EBRP: energy-balanced routing protocol for data gathering in wireless sensor networks." *IEEE Transactions on Parallel and Distributed Systems* 22.12 (2011): 2108-2125.
- [13] S. Kumar, T.H. Lai, J. Balogh, "On Kcoverage in a Mostly Sleeping Sensor Network", *Proc. ACM MobiCom*, pp. 144-158, 2004.
- [14] C. Hsin, M. Liu, "Network Coverage Using Low Duty-Cycled Sensors: Random and Coordinated Sleep Algorithms", *Proc. Third Int'l Symp. Information Processing in Sensor Networks (IPSN)*, pp. 433-442, 2004
- [15] Zhang, Haibo, and Hong Shen. "Energy-efficient beaconless geographic routing in wireless sensor networks." *IEEE transactions on parallel and distributed systems* 21.6 (2010): 881-896.
- [16] A. A. Abbasi and M. Younis, "A survey on clustering algorithms for wireless sensor networks," *Computer Communications*, vol. 30, pp. 2826–2841, 2007
- [17] J. S. Liu and C. H. R. Lin, "Energy-efficiency clustering protocol in wireless sensor networks," *Ad Hoc Networks*, vol. 3, no. 3, pp. 371– 388, May 2005
- [18] Wei, Dali, et al. "An energy-efficient clustering solution for wireless sensor networks." *IEEE transactions on wireless communications* 10.11 (2011): 3973-3983.
- [19] Karaboga, Dervis, Selcuk Okdem, and Celal Ozturk. "Cluster based wireless sensor network routing using artificial bee colony algorithm." *Wireless Networks* 18.7 (2012): 847-860.
- [20] Kuila, Pratyay, and Prasanta K. Jana. "Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach." *Engineering Applications of Artificial Intelligence* 33 (2014): 127-140.
- [21] Bagci, Hakan, and Adnan Yazici. "An energy aware fuzzy approach to unequal clustering in wireless sensor networks." *Applied Soft Computing* 13.4 (2013): 1741-1749.
- [22] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," *IEEE Hawaii International Conference on System Sciences*, pp. 4-7, Jan. 2000.
- [23] Logambigai, R. & Kannan, A., "Fuzzy logic based unequal clustering for wireless sensor networks", *Wireless Netw* (2016) 22: 945.
- [24] Bagci, H., & Yazici, A. (2013). An energy aware fuzzy approach to unequal clustering in wireless sensor networks. *Applied Soft Computing*, 13(4), 1741–1749.
- [25] Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In *Proceedings of IEEE 33rd annual Hawaii international conference on system sciences*.