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Wolf Nature and Neural Network Based WSN Energy Optimization in Dynamic Environment

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Abstract – Data collection from harsh environment is depend on sensor device network having wireless communication. Device working depend on battery life and energy dissipation depends on packet delivery in network. This paper has proposed a hybrid model to increase the energy utilization of nodes for WSN life enhancement. Due to dynamic nature of the work nodes clustering approach was used by the work. Wolf nature based genetic algorithm identifies cluster center nodes in WSN on the basis of available energy and distance from base station. Neural network was used by the model for classifying the nodes into fit and weak class. Neural network selected nodes were used in the wolf algorithm which ultimately cluster network. Experiment was on different combination of monitor area and number of nodes. Result shows that proposed has increases the life span of the model with high packet count as compared to other existing models of WSN energy optimization.

Keywords— Clustering, Genetic Algorithm, Neural Network, Wireless network.

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1. INTRODUCTION

Wireless sensor network is a popular area for research now days, due to vast potential usage of sensor networks in different areas. A sensor network is a comprised of sensing, processing, communication ability which helps to observe, instrument, react to events and phenomena in a specified environment [1]. This kind of network enables to connect the physical world to environment. By networking tiny sensor nodes, it becomes easy to obtain the data about physical phenomena which was very much difficult with conventional ways. The process of getting that information to a central place to process it, and then returning the result to the nodes requires communication. Radio communication used by WSN nodes is the largest consumer of the finite energy resources contained within a WSN node's battery [2].

Routing technique plays a vital role in the wireless sensor network. It is extremely difficult to assign the global ids for a large number of deployed sensor nodes. Thus, traditional protocols may not be applicable for WSN. Unlike conventional wireless communication networks (MANET, cellular network, etc.), WSN has inherent characteristics. It is highly dynamic network and specific to the application, and additionally it has limited energy, storage, and processing capability. These characteristics make it a very challenging task to develop a routing protocol [3, 4].

There are mainly two reasons responsible for the dynamic infrastructure. The first reason is the energy; the sensor nodes have limited energy in the form of batteries. If the protocol is unable to balance the load among the nodes, the sensor node could die. It leads to the dynamic network structure. The second reason is the mobility; in many scenarios after the deployment, sensor nodes are static but sink can move within the network. It makes the network dynamic, and the protocol that works for static sink may not be applicable for mobile sink [5].

The sole purpose of this paper is to find the method which is more energy efficient. As Wireless sensor networks are battery operated. Sensor nodes collect the data and pass them on to the network for further use. This passing and receiving of data utilizes most of the energy of the network. So for better operation and increase the lifetime of the network, energy consumption must be the major factor of concern.

2. RELATED WORK

Cheng et al. [6] developed a fast and efficient broadcast (FEB) protocol for asynchronous WSNs with mobile sink. The sink traveled along the sensing field in a predefined path depending on the coverage information that was shared with the sensor nodes before starting the transmission process. The authors argued that their proposed approach minimized the broadcast delay and reduced the energy consumption.

Ho et al. [7] applied particle swarm optimization to obtain the optimal WSN topology and UAV trajectory for reducing energy consumption. The proposed model was compared with a low-energy adaptive clustering hierarchy (LEACH) protocol to evaluate its performance. Though the framework considered a relatively flat terrain to model the radio communication, the radio model used in the literature can also be useful to design propagation models in other environments. Different from the other proposed models, the UAV is also utilized in this architecture to select the CH from the ground sensor nodes.

Gharaei et al. [8] developed energy-efficient mobile-sink sojourn location optimization (EMSLO) scheme for heterogeneous home network. Robovac is employed as a mobile sink, and the sojourn location was optimized to solve the energy hole and network coverage problems. The obtained results from their approach enhanced the coverage time and improved the network lifetime.

Zhong et al. [9] introduced a hyper-heuristic framework (HHF) that intelligently organized the mobile sink movements based on heuristic rules. Based on the prior knowledge of their networks, predefined low-level heuristics and training networks were designed and assigned as input to the genetic programming (GP) algorithm to automatically built-up highlevel heuristics. As a result, the GP algorithm produced the heuristics with the highest fitness.

Wang et al. [10] introduced a trajectory scheduling method based on coverage rate for multiple mobile sinks (TSCRM) that utilized particle swarm optimization (PSO) to find the optimal rendezvous points for the mobile sinks. TSCRM integrated the genetic algorithm (GA) for scheduling the traveling trajectory of the multiple sinks. The authors argued that the network lifetime enhanced due to the reduction in node's energy consumption.

Mohammed Al Mazaideh et. al. in [11] proposed acognitive sensing algorithm for efficient data transfer through WSNs, which uses multiple objective genetic algorithms (MOGA) to optimize the number of measurements, transmission range, and the sensing matrix. The algorithm aims at striking the right balance between energy-efficiency and accuracy. It constructs a path in a multi hop manner based on the optimized values. Numerical simulations and experiments show that Paretofront, which is the output of MOGA, helps the user to select the right combination of the number of measurements and the transmission range fitting the application at hand, and to strike a good balance between energy efficiency and accuracy.

The optimal WSN CH selection technique is observed in many studies [12]. Some other studies investigated the optimal trajectory problem for collecting WSN data [13], [14], while some studies were performed to localize the sensor nodes [15], [16].

3. PROPOSED METHODOLOGY

Explanation of the proposed WNNEO (Wolf Nature and Neural based Energy Optimization) model is done in this section. Table 1 shows a notation list to explains various steps of the energy optimization proposed model. Fig 1 is a flow chart of neural network training for the selection of fit nodes on the basis of (energy, position). Fig 2 shows the flow chart of the wolf algorithm for nodes cluster center selection after a fix number of rounds.

Table 1 WNNEO model notations.

Symbol	Meaning
N	Nodes
A	Area
E	Energy
TN	Trained Neural
C	Cluster center
k	Number of cluster
L	Number of bits in Packet
E_t	Energy need to Transfer L bits
P	Packet count of node
W	Wolf
m	Number of wolf in population
H	Hunting Vale of wolf
Pos	Position of Node in A

Develop WSN Environment

Wireless sensor nodes are placed in a fixed area A having dimensions in meters. As work is in dynamic nature hence each node may have a different size of the battery or energy storage, in other words, node energy E is not the same at the beginning of work. Randomly place N number of nodes within the A area of WSN. The position of the node plays an important role in energy dissipation for transferring data to the base station in the network. A fix packet size of L number of bits is considered in the work. So receiving cost (energy) Er of a packet is same for all nodes. But transferring cost of Et directly depend of d distance between source and destination node shown in Eq. 1 [17].

$$E_t = pLd^s + \alpha L \text{ ---------Eq. 1}$$

In eq. 1 α is energy required per bit for processing in node. p, s value depends on distance if d is greater than d^o s is 2 otherwise s is 4.

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Training of Neural Network

Neural network role is to categorize nodes into two classes first is strong nodes and other is weak nodes. This classification of nodes reduces the cluster head selection time of the model and increase the quality of wolf population. WSN nodes have different features out of those this work utilize current energy value and current position in A area. Apart from this number of packets transfer feature were also evaluate. Estimation of packet count was done by Eq. 2.

$$P_n^r = \frac{E^r}{E_t^r}\text{------------Eq. 2}$$

Where r^{th} round in the network, P is packet count for r^{th} round of n^{th} node. Traiing input feature vector looks like {E^r, d, P_n^r} where d is distance between n^{th} node position coordinates and base station position coordinates. Desired output is value either 1 or 0, where 1 shows that node is strong and 0 shows that node is weak.

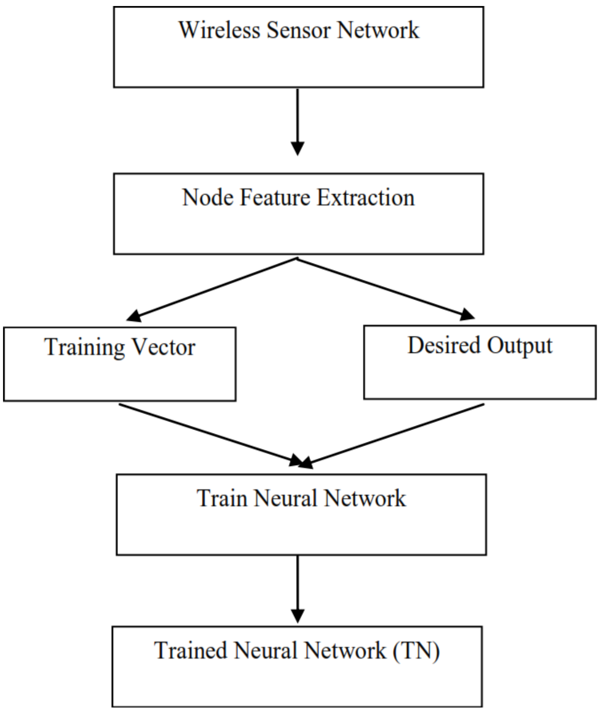


Fig. 1 Block diagram of neural network training.

This work considers three layer neural network architecture. Input layer have three neurons as per training vector size (Energy, distance, packet_count). Hidden layer has five neurons. Finally output layer has only one neuron. It's an completely connected architecture. This work uses soft-max activation function [17] for triggering the neuron. Output of training gives trained neural (TN) which takes node {E^r, d, P_n^r} value and classify it either strong or weak node class.

Wolf Nature Algorithm

In order to cluster nodes, model need cluster center. Due to dynamic nature of WSN genetic algorithm is adopt as no prior training required to find good solution. Based on the fitness value wolf genetic algorithm [18] classify chromosomes into four categories, hence chance of getting a good solution is high. This algorithm works on wolf hunting nature where alpha category wolf are need to be search from the group. In this model each chromosome is acting as wolf. Based on the fitness function wolf elements were change to get good cluster center.

Generate Wolf population: Wolf is set of k nodes in the network and collection of m number of wolf W is wolf population [19]. Wolf population is a matrix of mxk. Trained neural network TN has reduced the size of N by rejecting weak nodes. k is optimal cluster as per N number of nodes and A Value of k obtained from eq. 3 [20].

$$k = \sqrt{\frac{N\varepsilon_{fs}\times A}{2x3.124x(2x\alpha+E_A)}}\text{-----Eq. 3}$$

Where ε_{fs} is ideal amplifier power. W is obtained from Gaussian random distribution function.

$$W_m = \text{Gaussian}(m, k, N, TN)\text{----Eq. 4}$$

Hunting Value Each wolf has its own hunting efficiency, so this function finds the fitness of wolf hunting. Each wolf has set of cluster center nodes. Based on the minimum distance between non cluster center node NCN and cluster center nodes, NCN get clustered. Similarly all set of nodes were clustered into any of wolf set nodes. Now estimate energy dissipate to send one packet by NCN to the cluster center E_{NCND}. After that estimate energy dissipation of sending a packet to the base station from the cluster center node E_{CCD}. Summation of total energy dissipation is hunting value in the work.

$$H_m = E_{NCND} + E_{CCD}\text{----------Eq. 5}$$

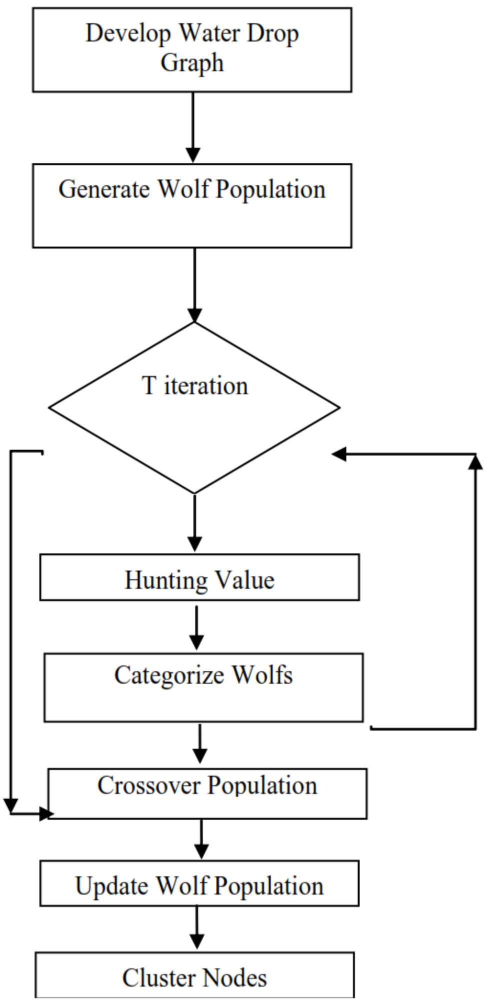


Fig. 2 Block diagram of WNA Clustering.

Categorize Wolf

Hunting value divide wolf population into four group alpha beta, Gamma, Delta such that $H_{alpha} > H_{beta} > H_{gamma} > H_{delta}$ Now wolf change position for prey 0 to 3 by eq.

$$A=P_w-rand*(P_w/Mt)*r-P_w-rand*(P_w/Mt) \text{-------Eq.6}$$

$$D=c.*(Delta-Alpha) \text{---Eq. 7}$$

$$P_1=Delta-A.*abs(D) \text{ ---Eq. 8}$$

Similarly

$$D=c.*(Beta-Alpha)$$

$$P_2=Beta-A.*abs(D)$$

$$P_3=Alpha$$

Final position shifting value estimate by Eq. 9

$$\boldsymbol{P_s}=\frac{\boldsymbol{P_1}+\boldsymbol{P_2}+\boldsymbol{P_3}}{\boldsymbol{3}} \text{---Eq. 9}$$

Crossover

As per shifting position P_s alpha wolf modifies the other wolf in the population. One of cluster center from the Alpha wolf set was select randomly and place at same position in the other wolf set. This operation done with all other wolf so new wolf increase the size of population. Population need to be update by estimating hunting value of new wolf and compare with parent wolf. If any of parent hunting value if lower than new wolf then remove weak wolf from population. This addition of new or removing of old wolf is population updation. Repeat this steps for T number of iterations to get good set of solution (Cluster center).

Cluster Nodes

Cluster center cluster nodes in the WSN. Once nodes get cluster then communication of sending sensor data start. This sending of data continue for a few number of rounds and update cluster center with new node position, energy values.

Proposed WNNEO Algorithm

Input: N, A, TN, Pos

Output: CN // Cluster nodes

1. K□Optimize_Cluster(N, A)
2. W = Gaussian(m, k, N, TN)
3. Loop 1:T
4. H□Hunting_Value(W, Pos)
5. S□Sort(H)
6. [Alpha, Beta, Gamma, Delta]□Categorize_Wolf(S)
7. W'□Crossover(Alpha, Beta, Gamma, Delta)
8. H□Hunting_Value(W', Pos)
9. W□Update_Population(H, W')
10. End Loop
11. CN□Cluster_Nodes(W, k)

4. EXPERIMENT AND RESULT

Implementation of proposed WNNEO was done on MATLAB platform. Experimental values was compared with existing model of WSN energy optimization MSGR [20] and **IWDEO** [21]. Hardware setup for experimental work have configuration of 4GB RAM, Intel I3 processor. In order to analyze models work various combination of Area (100m, 150m, 200m) and Number of nodes (70, 100, 120) were set.

Results

Table 2 First node out in WSN, round based comparison

NodesxArea	MSGR	IWDEO	WNNEO
80x100	485	9447	11175
80x 150	484	2662	4623
80x 200	481	1251	917
100x100	486	11139	15195
100x 150	479	2593	3197
100x 200	485	710	769
120x100	485	9519	10263
120x150	898	2151	2999
120x200	471	1217	884

Table 2 shows round instant when first node discharge in the WSN, it was obtained that proposed WNNEO model has higher number of rounds as compared to other existing models. Use of Wolf genetic algorithm has increases the clustering accuracy of work and this reduces the power requirement for communication. Fisrt node discharge in WSN model was improved by % as compared to IWDEO model proposed in [20].

Table 3 total packet transfer to the base station based models comparison.

Nodesx Area	MSGR	IWDEO	WNNEO
80x100	73046	762022	804093
80x 150	88510	182421	271276
80x 200	73479	135703	142243
100x100	117058	1259801	1513010
100x 150	95225	277072	438179
100x 200	91549	124208	156399
120x100	143204	1326297	1697767
120x150	134350	427397	599023
120x200	127648	266190	270804

Total packet transfer parameter values in table 3 shows that proposed WNNEO model has increases the packet count by % as compared to IWDEO and % as compared to MSGR. One more observation obtained from the resuts that increase in area size reduces the packet count. Further use of neurl network for cluster center selection increases the model packet delivery count.

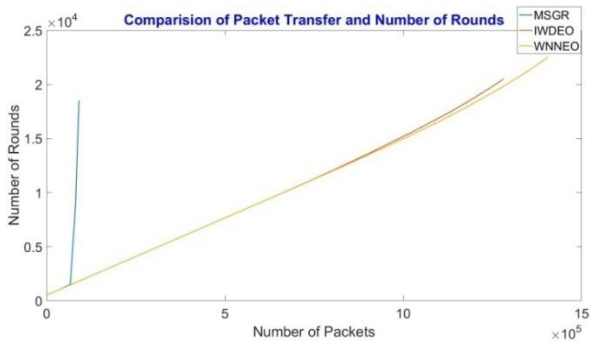
Table 4 Total number of rounds complete by models in whole life of WSN.

Nodesx Area	MSGR	IWDEO	WNNRO
80x100	8308	19676	22105
80x 150	15074	10059	15339
80x 200	6001	6432	7683
100x100	13869	20029	24485
100x 150	2885	9209	12551
100x 200	1499	4495	4307
120x100	10889	20676	21889
120x150	4160	11007	13915
120x200	973	6235	6831

When all set of live nodes transfer one packet to the base station is termed as round in WSN. So rounds directly shows that how long a network service when last node send its packet. Table 4 shows that proposed model has increases the percentage of total rounds by % as compared to IWDEO. Hrbrid use of neural network and wolf genetic algorithm increases the rounds count in dynamic WSN environment.

Table 4 Clustering time (Seconds) taken by models

Nodesx Area	MSGR	IWDEO	WNNRO
80x100	0.265	0.0626	0.0286
80x 150	0.338	0.0505	0.028
80x 200	0.192	0.0459	0.0241
100x100	0.1703	0.0999	0.0453
100x 150	0.322	0.0655	0.0304
100x 200			
120x100	02540	0.0795	0.0262
120x150	0. 67	0.0768	0.0322
120x200	0.68	0.088	0.0283



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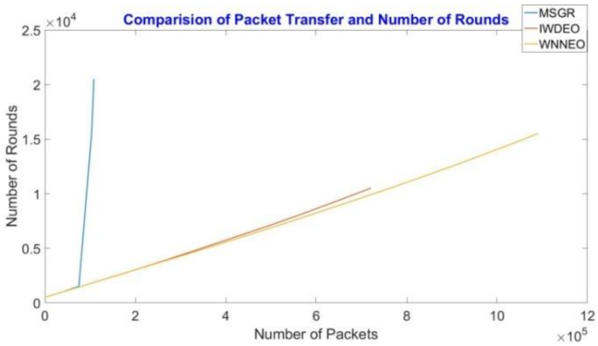

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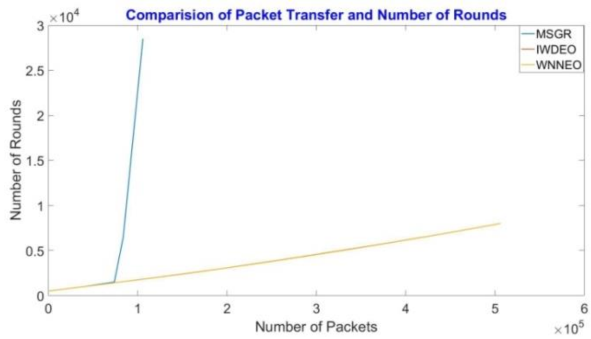

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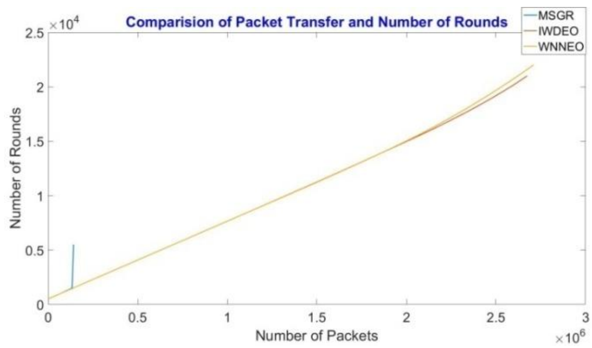

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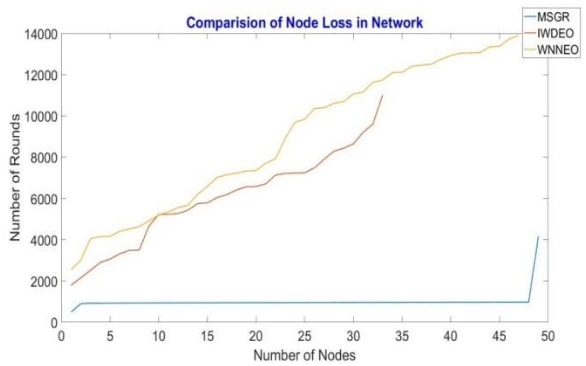

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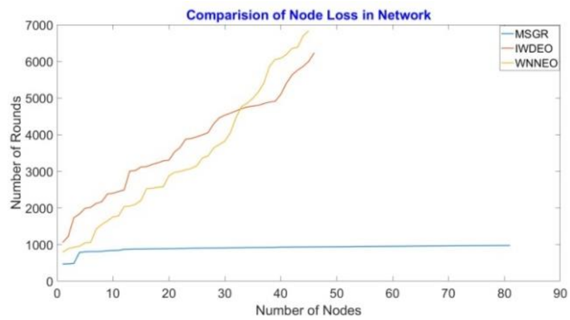

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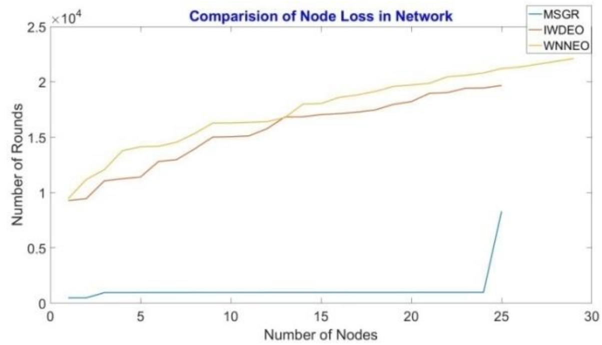
Fig. 3 Comparison of node loss with number of rounds.



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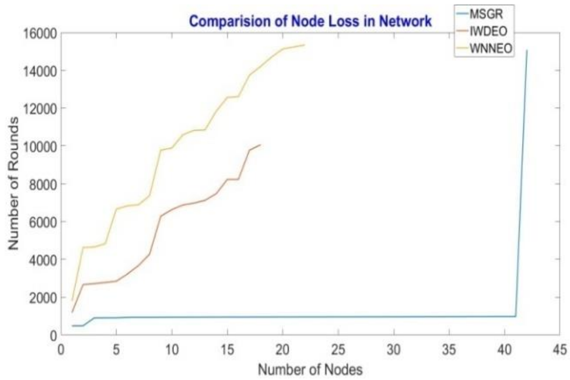

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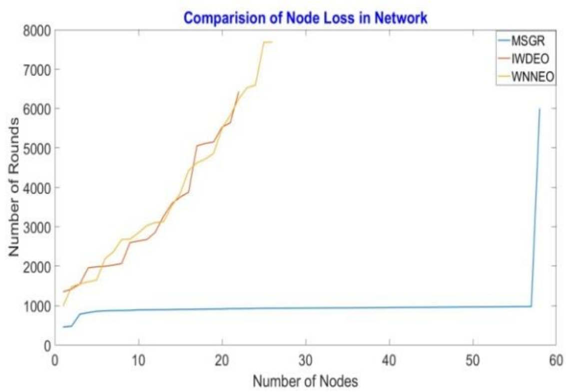

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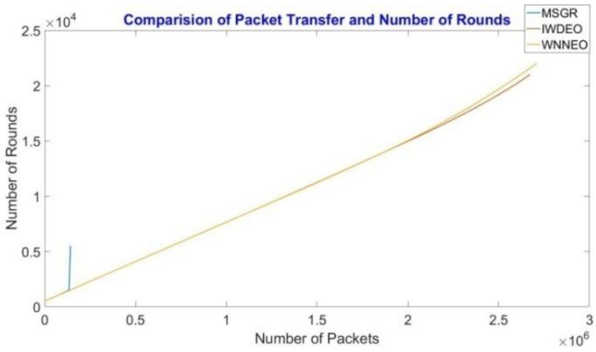

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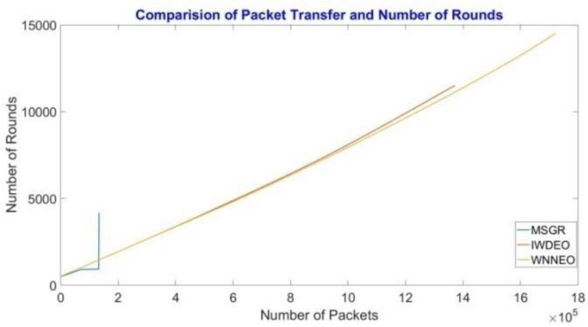

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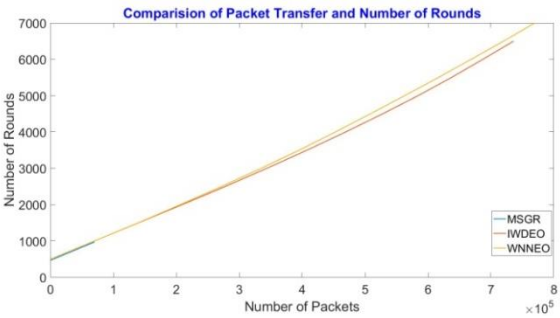

(f)

Fig. 4 Comparison of packet transfer with number of rounds.

5. CONCLUSION

Fig. 3 and 4 shows that packet count of proposed model is always high in different size of area and nodes. Similarly node loss of proposed model is less in low number of WSN round. Use of neural network for cluster center candidate node selection has directly increases the wolf clustering algorithm for any random situation.

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