Performance Analysis of KSOM-LEACH over WSN

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Abstract—The current development within the communication field lead to continuous and urgent needs for new data transfer techniques that can perform the communication process in a more reliable and secure manner. WSN emerged recently as a common and significant type of network which can be used within the environment that cannot be continuously managed by the human being. To enhance WSN performance in terms of several criteria, including; lifetime and energy, then several procedures can be employed, such as; clustering. KSOM emerged as a common technique for clustering in WSN. The aim of this paper is to evaluate the WSN performance in terms of average lifetime and consumed energy after adding Kohenon function of the neural network. Results show that the performance of the lifetime increased by 9.1% compared to LEACH protocol, while the energy consumed decreased by 3.03%.

Index Terms—Wireless Sensor Networks (WSNs); Kohenon Self Organizing Mapping (KSOM); Cluster Head (CH); Artificial Neural Networks (ANNs)

I. Introduction

In information industry, a pivotal role is played by Wireless Sensor Networks (WSN) especially in the 21st century due to its wide application in medical care, environmental monitoring, military as well as small home applications [1]. In WSN, an important component of power-consumption is routing protocol. A routing protocol needs power when transmitting and receiving data for the nodes. This power is regarded as the nodes' overhead. However, remote nodes cannot do data delivery without routing to the collector "Sink Node" [2]. There was revelation in this deficiency of the necessity to tailor routing protocols with reduced power consumption to achieve the goal of prolonging the sensor notes lifetime. A structure of a cluster-based network can help balance the network nodes' energy consumption. Low Energy Adaptive Clustering Hierarchy (LEACH) protocol is considered the most famous techniques of clustering in addition to being the first WSNs' clustering techniques. These WSNs protocols have been researched on how they can be used to help reduce the power consumption in network and extend the expected lifetime of the networks. The section prevent literature on different studies that have been conducted relating wireless sensor network LEACH.

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II. Previous Work

Authors in [3] studied trust-based LEACH protocols for Wireless Sensor Networks. The proposed protocol provided a routine that is secure while at the same time it preserved the important functionalities of the initial protocol. The proposed scheme decision-making was based on the decision trust, evaluated dynamically and separately for various decisions by basic trust simulations. The trust simulation was maintained by module of trust management that is integrated with a routing module that is trust-based, having novel technique in cluster-head-assisted and trust update module monitoring control. The simulation results of the study indicated that there is effectiveness in the proposed scheme in preserving energy and life of the network nodes.

In [4] the LEACH protocol and its improved algorithm are wireless sensor network was studied. In the paper, the energy factor was introduced during the selection of cluster head, which helped avoid a node consisting of energy that is very low to be cluster head. Meanwhile, the paper conducted simulations which are particular to LEACH protocol. This enhanced algorithm in terms of lifetime of the network as well as the networks stability, energy consumption as well as data packages collection. The results from simulations showed that the improved algorithm compared to LEACH protocol had better performance in these aspects.

Improvement on LEACH routing algorithm for wireless sensor networks was studied in [5]. In this paper, in improving the cluster head election random probability, the frequency of becoming cluster head and the residual energy factors were introduced. Hence, with the number time having been increased, the node consisting of fewer times and more residual energy of the becoming CH was more likely in the paper to be chosen as CHs, which would ensure balanced energy consumption. Finally, the results from the study demonstrated that the algorithm that has been improved had the capacity to outperform in the network lifetime the LEACH.

Further, the authors in [6] studied an energy efficiency optimised LEACH-C for wireless sensor network. By so doing, the paper proposed an optimized LEACH-C that is energy efficient. To begin with, a group of cluster heads was selected with the use of LEACH-C. Then, the acknowledgment and retransmission were taken into consideration to create a cluster head energy consumption model. The quadratic sum of distance was further calculated from each CH to member nodes in the solution considered as optimal. Finally, the paper estimated the largest consumption of energy for single CH in the round that followed and all the nodes consisting of larger residual energy than the consumption calculated taken to new simulation round annealing to look for a solution that is better. Thus, this way, the loss of CH for each of the rounds was able to be minimised and the lifetime of wireless sensor network can ultimately be extended.

[7] Further presented an improved cluster routing protocol for wireless sensor network through simplification. Specifically, the paper analysed improvement of LEACH-E and improved LEACH-EX by presenting LEACH's classical routing protocol. The Node's energy depletion in LEACH-E was balanced using two methods; first, the nodes current energy was considered when electing them as CH, then in each cluster, the number of nodes was limited. In LEACH-EX, the threshold formula used in CH election was simplified, and the results from the simulations indicated that formula (LEACH-EX) was effective and thus LEACH-EX was much better compared to LEACH-E and LEACH in terms of consuming energy and network's lifetime.

An optimized LEACH method for busty traffic in wireless sensor networks was presented by [8]. A new version of LEACH protocol known as OP-LEACH was presented in this study whose aim was reducing the consumption of energy within the wireless sensor networks. The paper evaluated both the proposed OP-LEACH and LEACH using OMNET++ simulator through extensive simulations which indicated that OP-LEACH had better performance in terms of extending the life of sensor networks and energy consumption. Furthermore, the paper found that the proposed OP-LEACH is very simple to understand and had better improvement in terms of data sent and time delays. Hence, the network throughput is improved in terms of sent data per frame and per slot average data sent. Thus, the method proposed in the study was found to be very resourceful when used in real networks.

Authors in [9] presented an improved LEACH protocol for data gathering and aggregation in wireless sensor network. To present this, the paper proposed a LEACH protocol that is improved for the purpose of data aggregation and gathering in Wireless sensor networks. Conventional LEACH in the paper was found to include cluster formation distribution, local processing in order to facilitate reduction of global communication and cluster-heads' randomized rotations. The new protocol proposed used multi-hope routing rather than the commonly used 2-hop routing in LEACH and further proposed the related algorithm. The simulation results from the paper demonstrated that the improved protocol proposed was more energy efficient compared to the ordinary LEACH.

Finally, an acknowledgment based system for forest fire detection via LEACH algorithm was proposed by [10]. Specifically, the paper presented an acknowledgment based system that would facilitate in management of disaster by use of wireless sensor network, which is able to sense the changes in environment. For the purposes of communication, LEACH algorithm has been utilized. Being hierarchical in nature, LEACH algorithm assists in maintenance of connection among the nodes, leading to communication that is effective. Considering that disaster is an activity, and its occurrence can happen any time and any place without having to give prior information and affect animals, property, and human no one can stop it. However, it is possible to develop a system that is able to alert human before it occurs saving property and many lives. The paper found out that the proposed sensor algorithm had the ability to save energy even when the temperature reaches threshold thus helping save energy by rouging the data continuously.

III. Formulation of the Problem

A. Protocol Flow Chart

As earlier noted, the purpose of the paper is modeling and designing a hybrid routing protocol that can be utilized within DWSN. The name of the new protocol that has been designed will be "Energy Efficient Optimized Routing Algorithm (EEORA)" whose particular goal is reducing the amount of energy that is consumed with the DWSN ensuring that there is efficient utilization of energy as well as transmitting efficiently data through the network. To achieve this, two major metrics will be reduced; these are the required distance to maintain, discover and use the routes and the sent amount of message within the network. The routing protocol proposed uses the benefits of hierarchal-based and flat-based routing protocol. Therefore the concept of the two routing protocol types is together combined. The primary EEORA idea is employing new clustering algorithm in DWSN splitting into a particular number of clusters as well as the use of the flat based routing concept while the new approach is applied in the communication of data stage that is primarily based on maximization of sensor nodes number that does data transmission.

B. Clustering Process

In dividing WSN into a number of clusters, the followed algorithm will be novel clustering. The process of clustering is started through the division of the whole WSN are into a particular number of the centric square. The performance of division is done to ensure that the distance between CH and Normal node and that between the BC and CH are reduced. The formation of the centric square is done in reference with BC coordinates that is assumed to be at WSN centre location with coordinate (X_0, Y_0). The number (k) concentric square is calculated by the use of shown equation in the flow chart shown previously and is dependent on mainly DWSN areas, the BS coordinates and that distance between the two successive concentric squares [11]. The k^{th} square dimension is calculated as shown in below equations.

$$T_R^{S_k}\ (x_1, y_1) = (x_0 +\ r_m, y_o +\ r_m) \quad (1)$$

$$B_R^{S_k}\ (x_2, y_2) = (x_0 +\ r_m, y_o +\ r_m) \quad (2)$$

$$T_L^{S_k}\ (x_3, y_3) = (x_0 -\ r_m, y_o +\ r_m) \quad (3)$$

$$B_L^{S_k}\ (x_4, y_4) = (x_0 -\ r_m, y_o +\ r_m) \quad (4)$$

In this case; $T_R^{S_k}$ denotes the k[th] squire in the top right, $B_R^{S_k}$ reflects the k[th] square in the bottom right $B_L^{S_k}$ denotes the K[th] square in the bottom right while $T_L^{S_k}$ is the k[th] square in the top left. On the other hand, r_m stands for between the boundary of K[th] square and BS distance as provided by the below equation.

$$r_m = m\ .r \quad (5)$$

Once the DWSN is changed to small squares that are concentric, a cluster is formed when the part around two boring squares are divided into four parts with the same dimensions, where for all the squares that are neighbouring, segmentation will be performed. In every cluster, a CH is chosen depending on the highest amount of energy that is residual, with the distance that is minimal among CHs and CH within all levels that are connected directly, which in the end forms WSN that is clustered.

In every cluster, one CH is assigned with a connection made between the nodes and the any of the CH neighbour, which will lead to a reduction in the distance that is required to reach the BS which will improve the WSN's lifetime.

C. Communication of Data

After the CH has been selected in every cluster and the clusters being formed, initiation of the data communication is done. The proposition of approach of the novel for communication of data is done, which can be put together as follows,

"Advertise Message (ADV)": when new data is sensed by the node and wants to do data sharing with the nodes that remain inside DWSN, then there is first employment of ADV message by the node with the goal of informing the network that it contains data that can be shared. Included in the ADV message is ID of the sender node, the ID of the receiver node and Hop Field No.

"Request Message (REQ)": When sharing the data, the concerned nodes/node in the data responds by sending a REQ message to ensure that sender is notified that the said node wants to receive sensor data by the node that sent the ADV message.

"Data Message (DATA)": After the node that undertook the initiation of information process through sending ADV message is notified that there exists a particular node that would like its data that has been sensed, then the data sharing starts by Data message transmission the metadata also included.

There is the continuous performance of the steps by all the inside WSN CHs until upon BS receiving the ADV message. Once the ADV message is received by BS, a REQ message is sent back in a reverse direction. When the REQ message is received by the sender, the data is ready now for transmitting to the destination from the source and follows the routing path that was earlier determined when REQ and ADV message in WSN is being transferred [12]. With regards to the consumption of energy when receiving and transmitting a message in the network, a model similar to the adopted in [IRRD] is copied. In the said model, the nodes energy is said to decrease due to the data transmission by a proportional amount to the distance between every two nodes, the process of communication included. Furthermore, the energy of the nodes is noted also to go down or decrease as a result of data reception.

The equations that follow below shows the calculation process for the energy consumed while a packet of size L bits is being exchanged.

$$E_{Tx}\ (d, x) = Eelec * L + \epsilon_{amp} * L \quad (6)$$

$$E_{Rx}\ (L) = E_{elec} * L \quad (7)$$

The calculation of ϵ_{amp} is done in relation to reference distance D_0 which equations below gives:

$$\epsilon_{amp} = \epsilon_{fs} * d^2, d \le d_0 \quad (8)$$

$$\epsilon_{amp} =\ \epsilon_{fs} * d^4,\ d \ge d_0 \quad (9)$$

In this case, the distance separating every two nodes is denoted by d, energy parameters corresponding to the process of communication are denoted by $\epsilon_{amp} and\ \epsilon_{fs}$. Electronic energy consumption is denoted by E_{elec}, while E_{Rx} and E_{Tx} stands for energy consumed as a results of packets received and consumed respectively.

IV. Performance Metrics

The network's performance is determined by performance metrics. Several of the used metrics in the current simulations include; throughput, end-to-end delay, packet delivery ratio scalability and network lifetime and energy consumption.

End-to-end Delay: Sum of the period of that a bit take in reaching its destination starting from the time it is sent from source. The sum of end-to-end delay is taken as combined transmission, propagation, queuing and processing time.

Energy Consumption: The sum of consumed energy by the sensor mode during the process of communication. The rate at which source of energy over time is drained is shown here.

Throughput: This represents any system whose measurements are done in Kbps. This is the received successfully packet at a given time.

Scalability: This is the system capable of handling increasing load amount. Scalability demonstrates the behavior of a network when there is an increase in network size.

Network Life: This is the network total span up to the time all the nodes die. The network durability is shown by lifetime of network.

A. Comparison Routing Protocols of WSN

In Fig. 1 and Fig. 2, the models of the systems for LEACH and LEACH-KSOM algorithms are shown respectively. LEACH-KSOM algorithms have been proposed in this paper which has also been extensively studied with the goal of improving the efficiency and performance of WSN. The cyna cycles stand for nodes' random distribution while the to the base station path is denoted by red lines. Fig. 1 representing the LEACH algorithm, there is eligibility of each node to turn to cluster head. The selection of cluster head is done in the round-robin fashion, and it is not possible for election of the same node as cluster head in the round that follows. In this manner, conservation of energy happens through the election of varying cluster heads at time that differs. In Fig. 2 representing LEACH-KSOM algorithm, the packet forwarding and clustering face are consisted. Selection of each cluster head is made in each segment and communication done only among the cluster heads.

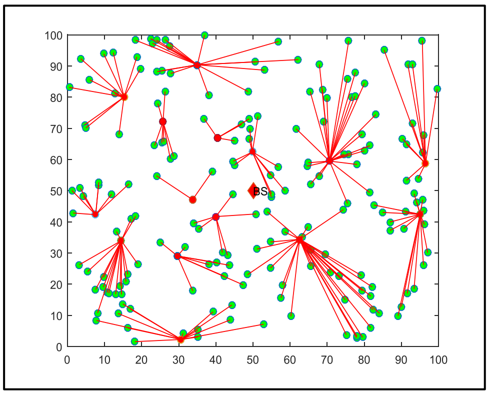

Fig. 1. LEACH protocol system model

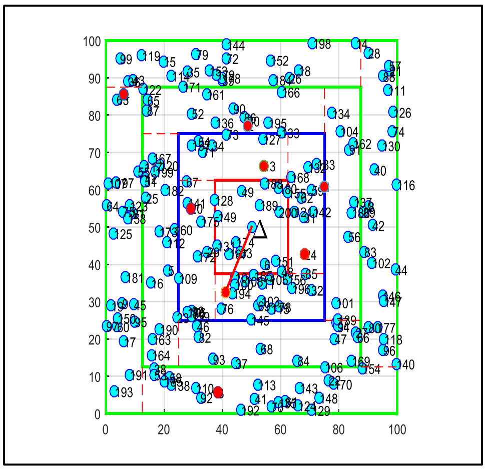

Fig. 2. LEACH-KSOM protocol system model

The following figure summarizes the research methodology.

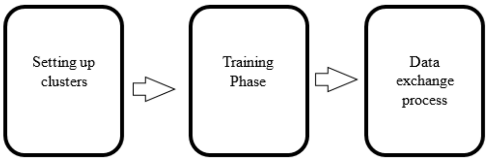

Fig. 3. The methodology of the research

The proposed scheme is initiated by the clusters' set up. This clustering will be performed via deploying SOM approach which will be followed by the applying of K-mean approach. Two main variables will be considered as the input dataset for SOM; these parameters are the nodes coordination within both energy level and network space named as x and y. As a result; a matrix that has dimension of $n \times 3$ can be formed; this matrix will be named as D. because of deploying different variable types; then these values must be normalized. The normalization process will be achieved via deploying the approach of normalization that is recognized as Min-Max approach. In this method; for element a; the maximum and minimum value are symbolized as $\max_a$ and $\min_a$. A value v can be mapped between (0, 1) via using equation 10 below:

$$V' = \frac{v - min_a}{(max_a - min_a)} \tag{10}$$

Now; regarding the weight matrix; it will be determined by BS via selecting m nodes which characterize with the maximum energy level; the selected nodes have identical values for the level of energy. The network space is able now be divided into several m regions, the node which is the nearest to the center will be latterly selected. Large value of m is required to be considered with WSNs because of deploying two SOM stages. The m nodes here can be selected in a random way. So; the weight matrix for the three variables can be written as given in equation below:

$$W = \begin{bmatrix} \frac{xd_1}{xd_{max}} & \cdots & \frac{xd_m}{xd_{max}} \\ \frac{yd_1}{yd_{max}} & \cdots & \frac{yd_m}{yd_{max}} \\ 1 - \frac{E_1}{E_{max}} & \cdots & 1 - \frac{E_m}{E_{max}} \end{bmatrix} \tag{11}$$

where;

W: is recognized as the SOM weight matrix.

$1 - \frac{E_1}{E_{max}}, \ldots.. 1 - \frac{E_m}{E_{max}}$: is recognized as the M selected nodes consumed energy. The following figure demonstrates the topology structure of SOM within WSNs. (Fig. 4)

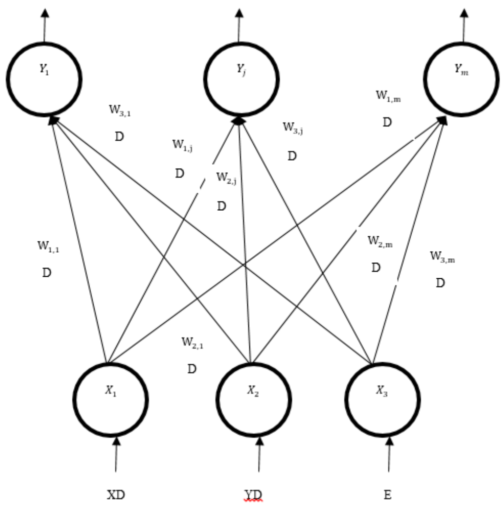

Fig. 4. Topology structure of SOM for the proposed scheme.

Regarding to the learning process within WSN; then it is performed based on Euclidian distance minimization among map prototype that has been given weight depending on h_{ij} or the neighborhood function and the input samples. As a result of this learning process; criterion must be reduced as much as possible, this criterion is illustrated below in equation 12 below:

$$E_{SOM} = \frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{M} h_{j,N(X^{(k)})} \left\|W_{.j} - X^{(k)}\right\|^2 \tag{12}$$

In the above equation; M is recognized as the number of units that have been used for mapping. $\mathrm{N}(\mathrm{X}^{(k)})$: is recognized as neuron which that owns the closest exhortation related to sample of data, h is recognized as the function of Gaussian neighborhood which can be defined as illustrated below in equation 13 below;

$$h_{i,j\,(t)} = exp\left(-\frac{\|r_j - r_i\|^2}{2\sigma_t{}^2}\right) \tag{13}$$

where;

J: map unit.

i: input sample.

$\left\|r_j - r_i\right\|^2$: is recognized as the distance that separates input sample and map unit.

σ_t: Recognized as radius of neighborhood that has been taken at t time. This radius can be defined deploying equation 14 below:

$$\sigma(t) = \sigma_0 exp\left(-{}^{t}/_{T}\right) = \tag{14}$$

In the above equation; t is recognized as the iteration number that is used in order to learn the network, T is recognized as the maximum iteration number during training process it can be also recognized as the length of training. The distance which separates the map neurons and vector of mapping are also calculated here. The competition phase winner is the neuron that characterizes with minimum distance regarding $\mathrm{X_k}$ input sample as illustrated below in equation 15 below;

$$N\,(X_k) = \arg_{1<j\leq m}\, min\, \left\|W_{.j} - X_k\right\|^2 \tag{15}$$

When the learning process initiated; σ_t characterizes with large value. While the algorithm time is increased, then this radius will be reduced. When the competition phase is finished; the winner's weight vector is updated using SOM. The update process also includes the winner vector neighbors who are located on $\mathrm{R}\,(\mathrm{N}(\mathrm{X_K}))$ neighborhood radius. Now;

$$W_{.j(t+1)} = \begin{cases} W_{.j}(t) + \alpha(t) h_{j,N(x_k)}(t)_k \left(x(t) - W_{.j}(t)\right); \\ \qquad when\ W_j \in R^{N(X_i)} \\ W_{.\,j}(t) \qquad ; \qquad otherwise \end{cases} \tag{16}$$

$\mathrm{h_{j,N(x_k)}}$: is recognized as neighborhood function that taken at t time. $\alpha(t)$: is recognized as the linear factor of learning which can be calculated as given below in equation 17;

$$\alpha(t) = \alpha_0\left(1 - {}^{t}/_{T}\right) \tag{17}$$

The initial rate of learning is symbolized by α_0. Iteration number is symbolized by t, and again T is training length. The learning process is continuously performed until no change is probable to occur within the weight vectors between sensor nodes. The SOM output will be latterly set as inputs for the K-means approach. During this approach; the data is divided into K clusters. K objects are randomly selected by K-mean approach in order to form and determine the centroids of the clusters. The smallest Euclidean distance will be latterly deployed in order to assign the objects within the established clusters. The process of computing the clusters' mean is performed continuously until no more change occurs within the centers of clusters. Equation 18 below demonstrates the minimized criterion with approach of K-mean;

$$E_{K-means} = \frac{1}{C}\sum_{K=1}^{C}\sum_{X\in Q_K}\|X - C_K\|^2 \tag{18}$$

C here is recognized as the clusters number within WSN and $\mathrm{Q_K}$ is defined as the cluster number $\mathrm{K^{th}}$. $\mathrm{C_K}$ is defined as the cluster $\mathrm{Q_K}$ centroid. Index of "Davies-Bouldin (DB)" is deployed in order to specify best clusters; number. Index of DS is defined as the ratio between dispersion of intra-clusters $\mathrm{S_c}$ to the distance of inter-cluster as illustrated below in equation 19 below:

$$I_{DB} = \frac{1}{C}\sum_{K=1}^{C}\max_{I\neq K}\left\{\frac{S_c(Q_K)+S_c(Q_I)}{d_{ce}(Q_K,Q_I)}\right\} \tag{19}$$

where;

$$S_c(Q_K) = \frac{\sum_i \|X_i - c_K\|^2}{|Q_K|} \tag{20}$$

$$d_{cl}(Q_K, Q_1) = \|c_K - c_1\|^2 \tag{21}$$

l and k : are the two clusters and $\mathrm{d_{cl}}$: distance that separates the centroids for these two clusters. In case that DB has small value; then this means that the related cluster is compact and characterizes with well-separated centres. The best number for the clusters is determined by the cluster numbers for which the index of DB is minimized as much as possible.

The training process is continuously performed until the normalized value of input vectors reaches the satisfactory level and will never be adjusted if the training process performed again. The training process can be also stopped after specific number of iterations. Two available approaches can be deployed in order to specify the similarity. The first approach is via weighting the input vectors by a specific weigh and then adding the resulted weights; which in turns considered as the particular neuron net input. Now; if this process is performed using N attributes; equation 22 below can be deployed in order to calculate net inputs;

$$net_{\,k} = \sum_{i=1}^{N}[x(i).\,w\,(i,k)] \tag{22}$$

$k:\ k^{th}\,neuron.$

N : $number\ of\ used\ attributes.$
$x(i), w(i)$: $directionsof\ \ unit\ vectors.$
$w(i,k)$: $the\ corresponding\ weight\ vectorof\ neurons$.

The second approach will be deployed in order to compute how much the two vectors are similar to each other. This will in turns be used in calculating Euclidean distance that was introduced in the previous sections as demonstrated below in equation 23;

$$net_{\ k} = \sqrt{\sum_{i=1}^{N} [x(i) - w\ (i,k)]^2}. \qquad (23)$$

When net is equaled to zero, then the two vectors are determined as identical ones. On the other hand; the vectors are assumed to be within opposite directions in case the net is equaled approximately twice normalized value for one of them. The winner node is selected to be the node that characterizes with minimum value for the Euclidean distance. The Conscience approach will be deployed here in order to prevent the nodes exceeding the limits for being selected as winner one. Now; assume the output for the neuron number i is given by equation 24 below;

$$y_i = \begin{cases} 1;\ \|w_i - X\|^{\,2} < \|w_j - X\|^{\,2} & ; i \neq j \\ 0 & ; elsewhere \end{cases} \qquad (24)$$

Depending on the number of times that node selected as winner node; a bias can be developed. This bias p is continuously adjusted based on equation 25 below;

$$p_i^{new} = p_i^{old} + \beta \left[y_i - p_i^{old} \right] \qquad (25)$$

β Here is a factor that must be selected within the range $0 < \beta \ll 1$; it is here assumed to be equals to 0.0001. Based on this; equation 26 below can be deployed to attain conscience factor or parameter as follow;

$$b_i = C\left(\frac{1}{N} - p_i\right) \qquad (26)$$

The final stage will be the update for both the winning sensor nodes weights and neighborhood nodes using equation 27 equation 28 below respectively;

$$w_{(n+1)}(k,j) = w_n(k,j) + \eta\ (n)[x(j) - w_n(k,j)] \qquad (27)$$

$$w_{(n+1)}(m,j) = w_n(m,j) + d\ (m,k,n)\ \eta(n) \qquad (28)$$

K here is recognized as the node that wins the competition; j is recognized as the attribute number. η (n) Is defined as modification.

B. Energy Consumption

The implementation of Energy Model is done to calculate the consumption of energy by each node. In the wireless sensor, the energy consumption is particularly as a result of event sensing as well as data transmission. Minimization of energy consumption has to be done due to its use as a critical resource for most of the nodes of the wireless sensor. The minimization of energy can be done through the avoidance of packet retransformation that is unnecessary. Optimum path is chosen by LEACH-KSOM which also reduces the packet's redundancy in different phases. The running of simulations happens for 50 rounds, and the obtained graph indicates that consumed energy for LEACH-KSOM algorithm is much lower than LEACH.

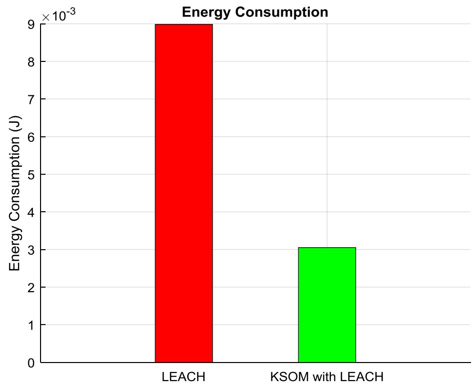

Fig. 5. Routing protocols of WSN energy consumption

C. Throughput

The system performance measurement is throughput. It is the sum of the received packets successfully within a period of time that is specified. Due to the fact that energy consumption is experienced at LEACH-KSOM, there are less dead nodes. Hence throughput is higher in this algorithm than the others. Reliable paths, as well as routes the data efficiency, are provided by LEACH-KSOM, leading to increase in the network's overall throughput. The throughput increment is as a result of path that is reliable to the sink. Equation 29 provides throughput.

$$\frac{Successful\ Received\ Packets}{time} \qquad (29)$$

D. Average End-to-End Delay

The system's end-to-end day is defined as the sum of taken time by the packet in reaching the designated destination from the sent time from its source. ADV and weighted techniques are implemented by LEACH-KSOM, phases of REQ for packet's successful delivery. The end-to-end delay is reduced by clustering in the system because packet directly receives through its cluster head that is nearest to the base station. Equation 30 provides the total end to end equation.

$$Delay = propagation\ time + transmission\ time + processing\ time + queuing\ time \qquad (30)$$

E. Scalability

Stability is capacity of handling the network's change. Stability is a metrics that is very critical that assists us in understanding the performance effect as a result of network change. To identify if the network has the ability to handle the network size increase, these parameters becomes critical. The network size increases lead to the increase in network load, control overhead and packet losses which are required for communication purposes.

Therefore, the resultant of this is overall performance decrease in the sensor network specifically if they are very large in size. The algorithm that we propose indicates that it has the capacity of handling the network size change without causing the overall system performance to decrease. The network size has varied in our simulations from 100-500, and the energy-delay, consumption of energy, throughput products change is measured.

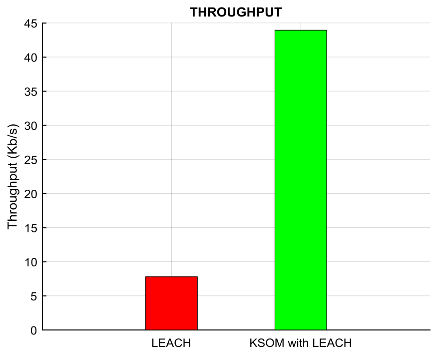

Fig. 6. Routing Protocols of WSN Throughput for

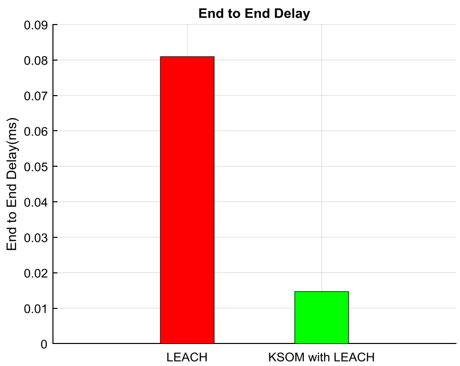

Fig. 7. End-to-end delay for routing protocols of WSN

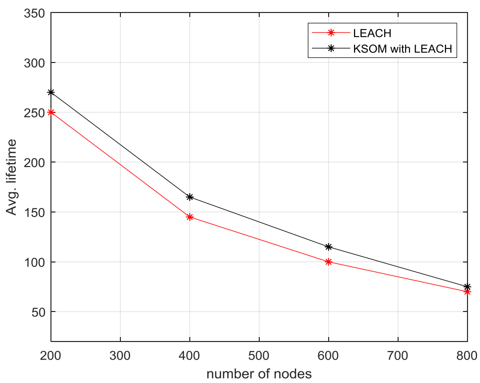

Fig. 8. The average lifetime for the WSN considering several numbers of nodes.

As Fig. 8 demonstrates, the increase in sensor nodes number increases in LEACH-KSOM the throughput. Since the nodes number increase increases the packet number that is reaching successfully the base station, there is a throughput increase. In Fig. 9, the nodes' consumption of energy is demonstrated with the network size increase. The figure evidence that the number of sensor nodes increase causes an increase in the number of consumed in the whole network. Since when there is more nodes number, it implies that over the entire network there is mode energy consumed, the consumption of energy rises with network size increase. Because LEACH-KSOM is energy efficient, in energy consumption, there is insignificant change with network size increase. The product of energy delays is acquired in Fig. 5 when energy consumed is multiplied with the network delay.

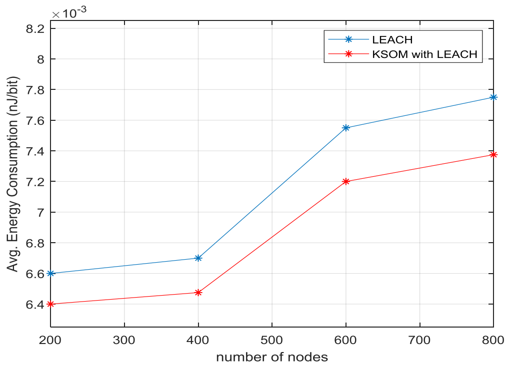

Fig. 9. Average energy for SOM, KSOM

V. The Results and the Discussions

In order to evaluate the designed system performance, a MATLAB code that simulates all the previous steps has been written and run. Three cases were considered during the implementation, which is; LEACH and LEACH-KSOM neural network. The network performance was evaluated using two main criteria, which are; the average lifetime and the average energy. The obtained results are now analyzed. The first obtained result is the average lifetime for the WSN as illustrated below in the following figure.

Fig. 8 illustrated the average lifetime for the WSN considering several numbers of nodes for LEACH and LEACH-KSOM neural network. As shown above, all curves have an inverse relationship with nodes number; so the average lifetime of the network decreases when the number of the nodes increases. For Kohenon case; the average lifetime is varied between 195 s and 45s for 200 nodes and 1000 nodes respectively, while it varied between 250 s and 65s for the same range. Finally; for LEACH-KSOM neural network; it can be easily noticed that this curve outperforms the two other curves; the lifetime is varied between 275s and 70 s for 200 nodes and 1000 nodes respectively.

The enhancement for the average energy due to applying LEACH-KSOM neural network with conscience function of neural network over LEACH-KSOM neural network can be calculated as given below considering 200 nodes;

$$enhancement = \left|\frac{KSOM_{\ lifetime} - LEACH_{\ lifetime}}{KSOM_{\ lifetime}}\right|$$
$$= \left|\frac{275 - 250}{275}\right| = 9.1\ \%$$

The second criterion that is used for the WSN performance evaluation is the average energy. Fig. 8 demonstrated the WSN performance in terms of this criterion for the three considered cases. The average energy is directly proportional to the number of the nodes; so when the number of nodes increases, then the average energy also increased. Again; KSOM performance is better than the SOM algorithm. Furthermore; adding the Conscience function to KSOM makes the WSN enhances performance in comparison with SOM and KSOM algorithms. The average energy in case of applying conscience function is varied between 1320 nJ/bit and 1625 nJ/bit for 200 nodes and 1000 nodes respectively. While it varied between 1360 nJ/bit and 1675 nJ/bit for 200 nodes and 1000 nodes respectively for KSOM algorithm.

The enhancement for the average energy consummation due to applying LEACH and LEACH-KSOM neural network can be calculated as given below considering 200 nodes;

$$enhancement = \left|\frac{KSOM_{\ energy} - LEACH_{\ energy}}{KSOM_{\ energy}}\right| = \left|\frac{1320 - 1360}{1320}\right| = 3.03\%$$

VI. Summary and Concluding Remarks

As a conclusion; WSNs performance in terms of the average consumed energy and average lifetime is considered critical and significant issue in WSN environment since the enhancement for this performance will result in increasing the ability for employing this type of network within several critical applications. As a future work; it is planned to evaluate the performance of WSN employing different clustering technique with KSOM algorithm.

References

[1] P. Rawat, K. D. Singh, H. Chaouchi, and J. M. Bonnin, "Wireless sensor networks: A survey on recent developments and potential synergies," *The Journal of Supercomputing*, vol. 68, no. 1, pp. 1-48, Apr. 1, 2014.

[2] C. T. Cheng, C. K. Tse, and F. C. Lau, "A clustering algorithm for wireless sensor networks based on social insect colonies," *IEEE Sensors Journal*, vol. 11, no. 3, pp. 711-21, Mar. 1, 2011.

[3] F. Song and B. Zhao, "Trust-based LEACH protocol for wireless sensor networks," in *Proc. Second International Conference on Future Generation Communication and Networking*, 2008, pp. 202-207.

[4] L. Xingguo, W. Junfeng, and B. Linlin, "LEACH protocol and its improved algorithm in wireless sensor network," in *Proc. International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery* (CyberC), 2016, pp. 418-422.

[5] L. Tang and S. Liu, "Improvement on leach routing algorithm for wireless sensor networks," in *Proc. International Conference on Internet Computing and Information Services*, 2011, pp. 199-202.

[6] S. Shi, X. Liu, and X. Gu, "An energy-efficiency Optimized LEACH-C for wireless sensor networks," in Proc. *7th International ICST Conference on Communications and Networking in China (CHINACOM)*, 2012, pp. 487-492.

[7] K. Naregal and A. Gudnavar, "Improved cluster routing protocol for wireless sensor network through simplification," in *Proc*. *18th Annual International Conference on Advanced Computing and Communications*, 2012, pp. 1-3.

[8] S. Gambhir and N. Fatima, "Op-LEACH: An optimized LEACH method for busty traffic in WSNs," in *Proc. Fourth International Conference on Advanced Computing & Communication Technologies*, 2014, pp. 222-229.

[9] W. Bo, H. Han-Ying, and F. Wen, "An improved LEACH protocol for data gathering and aggregation in wireless sensor networks," in *Proc. International Conference on Computer and Electrical Engineering*, 2008, pp. 398-401.

[10] S. Gupta and L. Doshi, "An acknowledgement based system for forest fire detection via leach algorithm," in *Proc*. *3rd International Conference on Computational Intelligence and Networks*, 2017, pp. 17-21.

[11] S. Oteafy and H. S. Hassanein, "Resource re-use in wireless sensor networks: Realizing a synergetic internet of things," *Journal of Communications*, vol. 7, no. 7, pp. 484-493, 2012.

[12] Hani, R. M. Bani, and A. A. Ijjeh, "A survey on LEACH-based energy aware protocols for wireless sensor networks," *Journal of Communications*, vol. 8, no. 3, pp. 192-206, 2013.

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