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Extending lifetime of wireless sensor networks using multi-sensor data fusion

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Abstract. In this paper a multi-sensor data fusion approach for wireless sensor network based on bayesian methods and ant colony optimization techniques has been proposed. In this method, each node is equipped with multiple sensors (i.e., temperature and humidity). Use of more than one sensor provides additional information about the environmental conditions. The data fusion approach based on the competitive-type hierarchical processing is considered for experimentation. Initially the data are collected by the sensors placed in the sensing fields and then the data fusion probabilities are computed on the sensed data. In this proposed methodology, the collected temperature tand humidity data are processed by multi-sensor data fusion techniques, which help in decreasing the energy consumption as well as communication cost by fusing the redundant data. The multiple data fusion process improves the reliability and accuracy of the sensed information and simultaneously saves energy, which was our primary objective. The proposed algorithms were simulated using Matlab. The executions of proposed arnd low-energy adaptive clustering hierarchy algorithms were carried out and the results show that the proposed algorithms could efficiently reduce the use of energy and were able to save more energy, thus increasing the overall network lifetime.

Keywords. Multi-sensor data fusion; optimization techniques; energy aware routing; ant colony optimization; wireless sensor network.

1. Introduction

The wireless sensor network (WSN) is a network of tiny embedded devices known as sensors that are connected wirelessly and can communicate wirelessly with each other. The applications of WSN are useful in many areas like health care monitoring, area monitoring, environmental/earth sensing (for agriculture), pollution monitoring, movements of terrorists in the high forest area (military), monitoring of LPG pipes laid in deep underwater, waste water monitoring, structural health monitoring and many more [1, 2].

The sensor devices of WSN are responsible for the transfer of information across the sensor network to the base station (BS), using some techniques that enhance the lifetime of the network by saving a substantial amount of energy. To reduce communication costs, we aimed to remove redundant sensor node information by multi-sensor data fusion (MSDF) method and avoid forwarding data that is of no use (known as redundant/dead-weight data). For instance, in sensing and monitoring applications, generally the neighbouring sensor nodes monitoring an environmental feature typically register similar values. In our proposed work we have considered the concept of MSDF for fusing the collected data before transmission occurs and ant colony optimization (AGO) techniques for efficiently routing the data from source to the BS using multi-hop routing techniques. The combination of these two techniques was experimented using Matlab simulations and the results proved that a substantial amount of energy could be saved. Section 1.1 gives an insight into the MSDF techniques in detail.

1.1 *MSDF*

The universal definition of fusion is to combine two or more distinct things. The term sensor fusion is the process of merging sensory data derived from different sources in a way that the resulting information is better than would have been possible when these sources were used individually [3]. In the architecture, shown in figure 1, there are often

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several hierarchical levels from where at the first level the information from active sensors is fed to the fusion centre, later the fusion of the data takes place and the fused information is passed to the BS.

Our focus was on the sensor data fusion, which merged numerical data from multiple sources probably measuring physically different things. The expectation was that MSDF is more informative and synthetic than the original data. The core objective was to prolong the network lifetime based on MSDF and ACO.

The main contributions of this paper are that it

- presents state-of-the-art advances in the design of MSDF algorithms, addresses issues related to the energy efficiency, delivers better packet delivery ratio (PDR) and extends the network lifetime of the sensor fields;
- describes new techniques in optimal MSDF and data dissemination;
- explores the topology, communication structure, computational resources, fusion levels and optimization of MSDF system architectures; also
- MSDF can be applied to any field of application where there is a need for prolongation of network lifetime;
- the new concept of having a node doing the dual role as a fusion centre and a cluster head (CH, with a capability to fuse low level data from multiple sources and dissemination of data to the BS);
- Bayesian fusion method is adopted as compared with other related work to yield better results (described in the later section of the paper);
- the clustering process adopted in the proposed scheme is unique where equal cluster areas are formed based on the chosen area for deployment and number of CHs needed (a unique distribution of sensors).

The remaining part of the paper is organized as follows. Relevant literature review in the field of MSDF and ACO including various analyses and research done has been discussed in section 2. Section 3 explains the proposed framework, which describes the formation of cluster and selection of CH methods, MSDF methods and finally data dissemination approach from source to BS. In section 4, implementation details have been mentioned from the initial set-up of the system to the result analysis in detail. Section 5 has the final conclusion delineating the uniqueness and strengths of the proposed system.

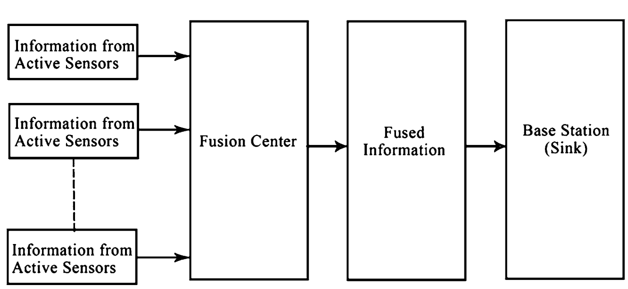

Figure 1. Architecture of multi-sensor data fusion system.

2. Literature review

Many researchers are working for improving the WSN lifetime. Various algorithms and protocols have been proposed in the published literature such as data aggregation, efficient scheduling and lot more to increase the lifetime of the network. Data fusion in WSN is still in the developmental stage and researchers globally have started developing algorithms based on data fusion such as cluster-H and tree-based data fusion techniques.

Zhai *et al* [4] proposed an algorithm Space Wireless Sensor Networks for Planetary Exploration (SWIPE), where two types of data are processed separately in the data fusion module. They talked about housekeeping and scientific data and how they are processed or fused depending on the need. A fuzzy-logic-based data fusion algorithm to infer the health status of a node is being proposed.

In [5], Hui-fang Chen *et al* proposed an algorithm of integration of cluster-based and adaptive data fusion in order to prevent the low reliability caused by CH node failure.

In [6], Kaihong Zhang *et al* have proposed the sensor node data fusion algorithm based on time-driven network data aggregation with the combination of sensor nodes scheduling and batch estimation. They proved that the reliability of the network data and network energy consumptions are better than those of Low Energy Adaptive Clustering Hierarchy (LEACH) and Threshold sensitive Energy Efficient sensor Network protocol (TEEN).

In [7], Chair and Varshney proposed a data fusion algorithm for local decision making using the minimum probability of error criterion. To implement the rule, the probability of detection and the probability of false alarm for each sensor must be known.

As per research work in [8–11] the use of data fusion technology can minimize the total energy consumption of the WSNs to a larger extent.

Nikolidakis *et al* [12] proposed a new protocol called Equalized Cluster Head Election Routing Protocol (ECHERP). This protocol pursues energy conservation through balanced clustering. ECHERP models the network as a linear system using the Gaussian elimination algorithm, and then calculates the combinations of nodes that are probable CHs in order to increase the network lifetime. This protocol was efficient in terms of network lifetime when evaluated against other well-known protocols. Hot spots in a WSN came into view, such as locations under heavy traffic load. Nodes in hot spot quickly ate up energy resources, leading to an interruption in the network. This problem was widespread for data collection in which CHs had an intense load of gathering and routing data. The routing load on CHs in particular deepened as the distance to the sink decreased. To balance the traffic load and the energy utilization in the network, the CH had to be alternated among all nodes and the cluster sizes were cautiously determined at diverse parts of the network. A distributed clustering algorithm called energy-efficient clustering that established suitable cluster sizes, depending on the hop distance to the sink, while attaining estimated equalization of a sensor node lifetime and reduced energy consumption was proposed [13]. One of the key concerns in WSN is routing due to the mobility of the nodes. Furthermore, the difficulty increases due to various characteristics like dynamic topology, time-varying Quality of Service (QoS) requirements, limited energy, etc. QoS routing plays a key role in providing QoS in WSNs. The biggest challenge in this kind of networks is to find a path between the communication endpoints satisfying the users QoS requirement. Nature-inspired algorithms such as ACO algorithms have been shown to be a good technique for developing routing algorithms for mobile ad hoc networks (MANETs).

In Roy *et al* [14], a new QoS algorithm for MANET has been put forth. This proposed algorithm combined the idea of ACO and optimized link state routing (OLSR) protocol to identify multiple paths between source and destination nodes. Dynamic Traffic Routing (DTR) refers to the process of redirecting traffic at junctions in a traffic network resultant to the developing traffic conditions as time progresses [15].

Considering the DTR problem for a traffic network as a directed graph, the process deals with mathematical facet of the resulting optimization problem from the viewpoint of network theory. Networks have thousands of edges and nodes, resulting in a considerable and computationally complex DTR optimization problem. ACO was chosen as the optimal method to solve problems in [16].

However, the standard ACO algorithm is not capable of solving the routing optimization problem; therefore a new ACO algorithm was developed to attain the goal of finding the best distribution of traffic in the network [15]. The key differences of WSNs compared with other networks were limited energy resources and relatively low processing capabilities. Therefore, running power and reducing energy utilization are of great significance in WSNs. In [17], the authors Jafari and Khotanlou presented a method for WSN routing, which can be more effective regarding the criteria of path length, delay and sensor node energy for the quality of service. The proposed method used an ant-colony-based routing algorithm and local inquiry to find optimal routes. A fuzzy inference system was also used to decide the route superiority.

3. Proposed framework

The proposed framework is divided into three phases. In the first phase the CH selection and cluster formation is described in detail by considering the area of the network and number of clusters to be formed. In the second phase the data fusion Bayesian method is described considering two types temperature and humidity of sensors. In the third phase, data routing from source to destination is described considering the ACO techniques. All the three phases are illustrated below.

3.1 *Phase I: CH selection and cluster formation approach*

In clustering architecture, the sensors are grouped together to form a cluster as per the given conditions and one node acts as CH. The clustering algorithm partitions the network into smaller areas called clusters. The CH selection and cluster formation algorithm is described in algorithm 1.
3.1a *CH selection and cluster formation*:

```
Algorithm clustorFormation(Integer NoR)
//NoR is Number of Rounds as Input
  to the algorithm
 {
Integer A  //Area of Network
Integer Cn //No. of Cluster to be formed
Integer Ac //Area of Cluster
Integer NoN //Number of nodes in
total area of Network

Read(A);
Read (Cn);
// Calculate the area of each cluster
    Ac = A/Cn;

//Randomly deploy the sensor nodes
 in network area;

For (k=1 to NoN) do
{ Setup the energy and
  the location of each node.
} For (c=1 to NoR) do
{
CH = Highest energy node
     of the Clusters.
      CH Broadcasts advertising messages to
all the nodes of cluster area Ac.

Cm sends acknowledge message to CH;
//Cm are cluster member sensor nodes;

CH calculates  d(CHi,nodej);
//CHi is CH of ith cluster and
all nodes j in that cluster.

CH and all Cm are synchronized
for further communication.
}
}//end of algorithm.
```

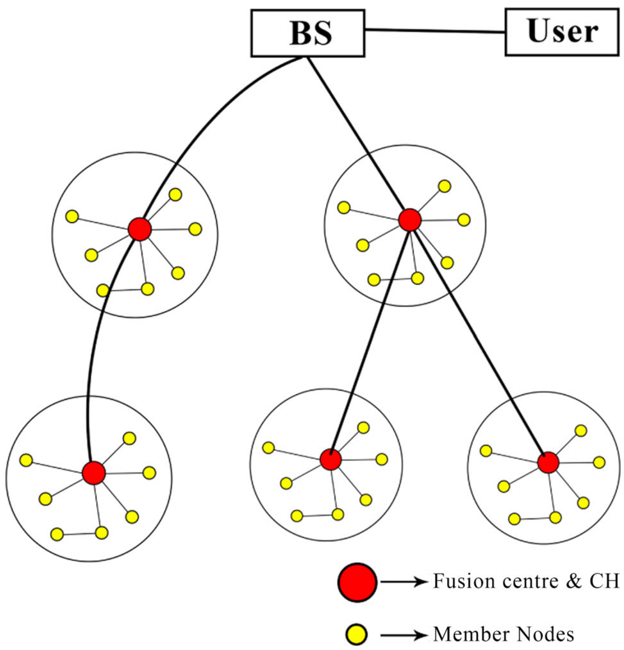

Figure 2. Data fusion framework for event detection (competitive type).

As an example, to calculate the cluster area, we consider the following parameters:

area (A) $= 500 \times 500\,\mathrm{m}^2$,

number of CH: $Cn = 5$,

each cluster area = $\frac{A}{Cn} = \frac{500 \times 500\,\mathrm{m}^2}{5} = 100 \times 500\,\mathrm{m}^2$.

After clustering is done, the data transmission starts by allowing the cluster members to send data to the CH and then from CH to the BS. The formation of clustering is repeated periodically whenever the data transmission is completed.

3.1b *Theoretical analysis*: Algorithm 1 has been analysed with respect to time and space complexity. Algorithm 1 has two loops that are nested. If we assume the number of nodes to be N and number of rounds to be M, then the time complexity of this algorithm is $O(NM)$. Except for the loop, all other statements get executed linearly and will contribute only constant time, which can be ignored asymptotically. Hence

$T(N) = O(NM)$.

The space complexity is the space required to store the total number of nodes in the network and it is obviously N. Hence space complexity will be $O(N^2)$ units of memory.

3.2 *Phase II: data fusion approach*

In our proposed system, MSDF fuses data from two sensors, namely temperature and humidity sensors. MSDF basically mixes the inputs from multiple sensors in order to provide better energy utilization. This fusion of sensors can be performed in multiple ways; we have carried it out by considering the mean and variance of the sensor values and thus they become the probability bounds of the sensor fusion. When we know the probability p of every value x then we can calculate the mean of X and variance of X as shown in the following equations:

$$\mu = \Sigma xp, \tag{1}$$

$$Var(x) = \Sigma x^2 p - \mu^2. \tag{2}$$

The application model considered for this work consists of a single BS and multiple sources of data receivers. The sensor nodes are wirelessly connected; hence they can communicate with each other through multi-hop communication to reach the BS. The sensor fusion network architecture that has been considered is of competitive type, which is called hierarchical processing as shown in figure 2.

Here each sensor node delivers independent dimensions of the same features. In this competitive type processing architecture, the CH plays a dual role, as fusion centre and a CH at the same time; it collects the sensed data from multiple member nodes, fuses all the collected data based on a decision criterion and then transfers the fused data to the BS through multi-hop shortest path routing mechanism based on ACO algorithm. Thus, this method reduces the computational workload, traffic load, consumes less bandwidth and increases the lifetime of the network by conserving the sensor nodes energy, which ultimately increases the network lifetime.

3.2a *The fusion process of data from two sensors using Bayesian methods*: Most current data fusion methods employ probabilistic descriptions of observations and processes and use Bayesian methods to combine this information.

Each sensor senses the event data and passes it to the CH of the respective clusters. The CH node usually does not send data as soon as it is available since waiting for member nodes to send more sensed data may lead to better data aggregation opportunities, which in turn improves the performance of the algorithm and saves energy. The responsibility of the CH is to compare the new data set with the old data set and carry out the fusion process, considering some prior probabilities.

To illustrate this concept, let us assume that there are two sensors: one is temperature and the other is humidity; both are sensing and sending the data to the CH; then the fusion process will take place based on the current measurement and the previous measurement.

Sensor 1:

S_{nd1} = new data set,

S_{od1} = old data set,

S_{cd1} = current sensed data.

Sensor 2:

S_{nd2} = new data set,

S_{od2} = old data set,

S_{cd2} = current sensed data.

At the fusion mode, the probability of a particular data x (e.g., temperature/humidity) can be computed based on the latest set of data using Bayes rules as

$$p\left(\frac{x}{S_{nd1},S_{nd2}}\right)=p\left(\frac{x}{S_{cd1}S_{cd2}S_{od1}S_{od2}}\right),$$

$$p\left(\frac{x}{S_{nd1},S_{nd2}}\right)=\frac{p\left(\frac{S_{cd1}S_{cd2}}{x,S_{od1}S_{od2}}\right)p\left(\frac{x}{S_{od1}S_{od2}}\right)}{p\left(\frac{S_{cd1}S_{cd2}}{S_{od1}S_{od2}}\right)}.$$

As sensor measurements are independent of each other, we get this as

$$\frac{p\left(\frac{S_{cd1}}{x,S_{od1}}\right)p\left(\frac{S_{cd2}}{x,S_{od2}}\right)p\left(\frac{x}{S_{od1}S_{od2}}\right)}{p\left(\frac{S_{cd1}S_{cd2}}{s_{od1}S_{od2}}\right)}$$
$$=\frac{p\left(\frac{x}{S_{nd1}}\right)p\left(\frac{S_{cd1}}{S_{od1}}\right)p\left(\frac{x}{S_{nd2}}\right)p\left(\frac{S_{cd2}}{S_{od2}}\right)p\left(\frac{x}{S_{nd1}S_{nd2}}\right)}{p\left(\frac{x}{S_{nd1}}\right)p\left(\frac{x}{S_{nd2}}\right)p\left(\frac{S_{cd1}S_{cd2}}{S_{nd1}S_{nd2}}\right)}.$$

At the fusion node

$$\frac{p\left(\frac{x}{S_{nd1}}\right)p\left(\frac{x}{S_{nd2}}\right)p\left(\frac{x}{S_{od1}S_{od2}}\right)}{p\left(\frac{x}{S_{od1}}\right)p\left(\frac{x}{S_{od2}}\right)}$$

is the required fusion solution at fusion centre.

Once the fusion of data is done, the fused data, which are small in size, are transmitted to the BS via multihop communication as discussed in phase III.

3.3 *Phase III: data dissemination approach*

Swarm Intelligence (SI) is the collective behaviour of decentralized, self-organized systems, natural or artificial. One of the concepts of SI is ACO, introduced by Dorigo and Sttzle in [18], a doctoral dissertation, which is a meta-heuristic for solving tough optimization problems, modelled on the actions of an ant colony. ACO is a probabilistic technique useful in problems that deal with finding better paths through graphs. Simulated ants locate optimal solutions by moving through a parameter space representing all possible solutions. Natural ants lay down pheromones directing each other to resources while exploring their environment. The simulated ants similarly record their positions and the quality of their solutions, so that in the later simulation iterations, more ants locate better solutions[19].

To route the fused data from source to BS, we used forward ants and backward ants to discover routes from source to the BS. In this method, node with the highest energy and highest pheromone levels are used for deciding the probability of the next node to be selected, which will have the minimal distance and maximum node energy to ensure a higher network lifetime.

The cost matrix of nodes minimal distance and maximum energy is shown in Algorithm 2. Now assume

$N=(n_1,n_2,n_n)$, to be the set of nodes;

$p(i)=$ probability of node n_i for forward ant to forward the data;

$PH(i)=$ pheromone value of node n_i;

$PH(i)=0$ for all $i=0$ to n.

When backward ant travels through node n_i

$$PH(i)=PH(i)+\alpha,$$

where α is a constant.

Routing table R, maintained at each node, then routing entry will be

$$R(i)=\{n_i,RE(i),PH(i)\},$$

where $n_i\in N$,

$RE(i)=$ remaining energy of node n_i and

$PH(i)=$ pheromone value of node n_i.

Now Probability $p(i)$ of selecting n_i as the next node for forward ant as well as data is

$$p(i)=\frac{PH(i)+RE(i)}{Max(PH)+Max(RE)}.$$

This probability is calculated periodically, giving equal priority to the shortest path and energy, which leads to an energy efficient path. Figure 2 shows how the fused data are routed from source to BS, using multi-hop communication.

3.3a *Algorithm 2*: *cost matrix of node distance and energy*

```
CostMatrix = zeros([num_nodes num_nodes]);
for i=1:num_nodes
x1 = node_x(i);
y1 = node_y(i);
energy = node_energy(i);
for j=1:num_nodes
x2 = node_x(j);
y2 = node_y(j);
if(i == j)
CostMatrix(i,j) = 0;
continue;
end
distance = pdist([x1 y1;x2 y2]);
cost = distance / energy;
CostMatrix(i,j) = cost;
end
end
```

3.3b *Theoretical analysis*: Algorithm 2 has been analysed with respect to time and space complexity. Algorithm 2 has two “for” loop which iterate `num_nodes` time. If we assume the number of nodes to be N, then as the two loops are nested, the time complexity of this algorithm is $O(N^2)$. Except loops all other statements get executed linearly and take only a constant time, which can be ignored asymptotically, i.e., $T(N) = O(N^2)$.

The space complexity will be the space required to store the total number of nodes in network and it is obviously N. Hence, space complexity will be $O(N^2)$ units of memory.

4. Implementation of proposed system

The proposed algorithm has been evaluated through simulations in Matlab for better performance in terms of network energy left, network energy Consumption per round and energy left in each node. Simulation parameters used for evaluation are presented in table 1.

The energy consumption model of the proposed system is described here. Some assumptions made are as follows:

1. the BS is stationary, has infinite power and located outside the sensing field for the proposed network model;
2. all sensor nodes are homogeneous in nature, having similar processing/communication capabilities;
3. all sensor nodes are supplied with the same initial energy;
4. all sensor nodes are stationary and unattended once they are deployed;
5. all sensors are capable of playing dual roles as fusion centre and CH;
6. all sensors can operate in active mode or low-power sleeping mode.

Case 1: Energy required for transmitting a data packet from a single member node to CH:

$$ET_{mnch} = E_{tx} l_a + \epsilon_{amp} l_a (d_{mnch})^2.$$

Case 2: Total energy required for transmitting a data packet from all the member nodes to CH:

$$ET_{Allmnch} = \left(\frac{n}{k} - 1\right) ET_{mnch}.$$

Case 3: Total energy required to receive all data packets at CH:

$$ER_{ch} = \left(\frac{n}{k} - 1\right)(E_{rx} l_a) + \epsilon_{amp} l_a.$$

Case 4: Energy consumption of multihop communication from CH to CH to BS:

$$\begin{aligned} ET_{total} =& E_{tx} l_{aF} + \epsilon_{amp} l_{aF} m^2 + E_{rx} l_{aF} + E_{tx}(l_{aF} + l_{bF}) \\ &+ epsilon_{amp}(l_{aF} + l_{bF}) m^2 \end{aligned}$$

Therefore the total network residual energy for multihop communication at any time (t) is

$$TNE^t_{residual} = \frac{(nE_i)^t - ET_{total}}{(nE_i)^t}.$$

The legends are shown in table 2.

The result analysis of the proposed algorithm against LEACH is described here. Initially 100 sensor nodes are deployed in the sensing field randomly. After execution of the algorithms, the figures 3–6 were obtained.

In figure 3 we observe that the residual energy of each node is far better when the MSDF algorithm is used as compared with the LEACH algorithm. The results shown in the graphs are the residual energy after 100 rounds of execution. The graphs clearly indicate this.

In this the average communication energy is calculated for each round starting from round 1–100. Figure 4 shows that the required communication energy is much less when MSDF is used as against the LEACH algorithm. The graphs clearly depict that there is a lot of energy saved when MSDF mode is used for communication. This ultimately increases the network lifetime.

In figure 5 we plot the total network energy (lifetime of the network) by calculating the number of alive nodes in the system against time in seconds. This helps in calculating the

Table 1. Simulation parameters.

Parameter	Values
Network area	500 m × 500 m
Number of nodes	100
Number of clusters	05
Initial energy	100 J
Transmission energy	0.1 mJ
Receiving energy	0.05 mJ
Sleep energy	0.0001 mJ
Transition energy	0.05 mJ
Rounds	100
Packet size	512 bytes
Transmission range	100 m
Rate (data transmission)	1 mbps

Table 2. Legends.

Symbol	Description
E_i	Initial node energy
ET_{total}	Total energy consumed by network
E_{tx}	Transmitter electronics
E_{rx}	Receiver electronics
ϵ_{amp}	Transmit amplifier
$(d_{mnch})^2$	Distance between member node and CH
l_a	Data
l_{aF}, l_{bF}	Fused data
n	Number of nodes
k	Number of clusters
$(\frac{n}{k} - 1)$	Number of possible nodes in cluster
m^2	Distance between CH–CH and CH–BS

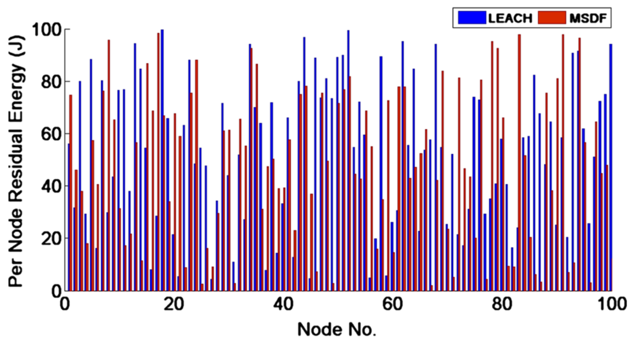

Figure 3. Per node residual energy (J).

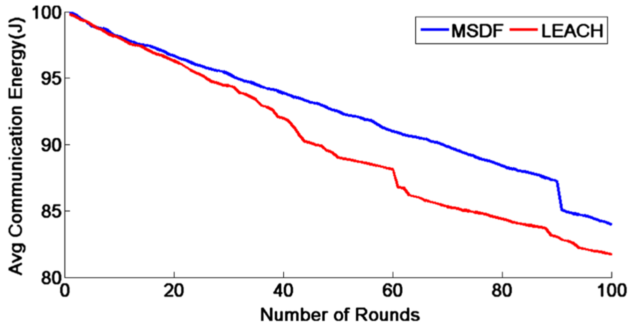

Figure 4. Average communication energy (J).

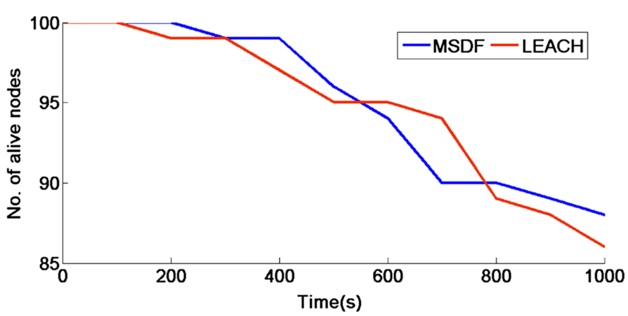

Figure 5. Network lifetime.

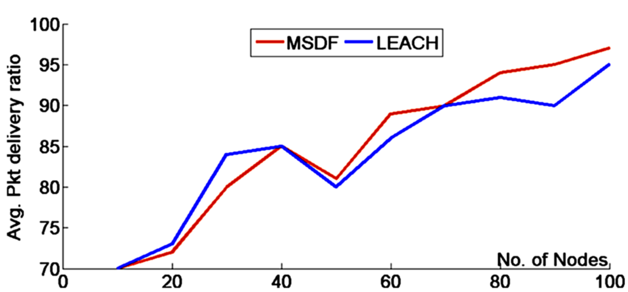

Figure 6. Average packet delivery ratio.

length of period the network will be up and in running condition. The MSDF and LEACH algorithms are applied and the results noticeably show when the MSDF algorithm is able to prolong the lifetime of the network as compared with LEACH.

Figure 6 illustrates the average PDR with respect to the number of sensor nodes for the proposed algorithm (MSDF) and LEACH. The graph obviously indicates that the proposed algorithm has 97% of an average PDR as compared with LEACH.

5. Conclusions

In this paper, we presented a novel way of saving energy by exploiting data fusion technology for WSNs. We designed an energy aware routing based on MSDF, which can fuse the data at the fusion centre and is able to deliver better results based on the ACO techniques for WSN with probability of route selection based on pheromone and left-over energy.

The simulation results proved better residual energy, requirement of lesser communication energy, better packet delivery ratio and prolongation of overall network lifetime with MSDF as compared with LEACH. Thus, our proposed method is more energy efficient; it saves a lot of energy and ultimately prolongs the network lifetime.

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