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Maximizing the Lifetime of Wireless Sensor Networks through Intelligent Clustering and Data Reduction Techniques

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Abstract—Wireless sensor networks are generally deployed in remote areas where no infrastructure is available. This imposes the use of battery operated devices which seriously limits the lifetime of the network. In this paper we present a cluster-based routing algorithm which is based on Fuzzy-ART neural networks to maximize the life span of such networks. Results show that the energy saving obtained improves the network lifetime by 79.6%, 17.1% and 22.4% (in terms of First Node Dies) when compared to LEACH, a centralised version of LEACH and a self-organizing map (SOM) neural network-based clustering algorithm respectively. Furthermore, this paper explores the use of a base station centric predictive filtering algorithm to reduce the amount of transmitted data leading to a further increase in network lifetime.

***Index Terms*—Fuzzy-ART neural networks, clustering algorithms, wireless sensor networks, predictive filtering.**

I. INTRODUCTION

WIRELESS sensor networks consist of hundreds of low-power, low-cost, multi-functioning sensor nodes operating in an unattended environment with limited energy supply and computational power. Such limitations coupled with the deployment of a large number of sensor nodes pose a number of challenges to the design and management of these networks, requiring energy-awareness at all layers of the networking protocol stack. Research on the issues related to the physical and link layers focus on system-level energy awareness, such as in [1-5]. On the other hand, recent work on the network layer focuses on energy-efficient route setup protocols that reliably relay data from the sensor nodes to the base station whilst maximising the lifetime of the network. Conventional techniques such as direct transmission have to be avoided because the energy loss incurred can be large and dependent on the location of the sensor node relative to the base station. Furthermore, using conventional multi-hop routing protocols such as Minimum Transmission Energy (MTE) [6, 7] will also result in an equally undesirable effect as the nodes closest to the base station will rapidly drain their energy resources as they are involved in relaying a large number of messages to the base station. In order to minimise these problems, various routing protocols have been proposed for wireless sensor networks. An in-depth survey of such protocols can be found in [8].

An effective approach to maximize the lifetime of a wireless sensor network is to reduce the transmission distance of each sensor node and to reduce the amount of transmitted information through the use of cluster-based routing algorithms. These algorithms reduce energy dissipation by selecting the optimal cluster heads and by reducing the amount of transmitted information through in-network processing. In this paper, we present NACHO (Neural Assisted Cluster Head Organisation), a novel cluster-based routing algorithm which uses a Fuzzy-ART neural network to elect optimal cluster heads. A number of mechanisms are employed to minimize the energy dissipation and improve energy balancing between the nodes to maximize the network lifetime. These include cluster head separation, neural network assisted cluster head election, cluster head rotation, and a novel load balancing cost function.

The rest of the paper is organised as follows: Section II gives a summary on related work; Section III describes the energy and radio model used in this work; Section IV gives a thorough description of the NACHO algorithm; Section V gives an in depth description of the base station centric predictive filtering algorithm; Section VI evaluates the performance of the complete system while Section VII provides some comments and conclusions.

II. RELATED WORK

Cluster-based routing algorithms are generally divided into two categories; centralised and distributed algorithms. One of the most popular distributed algorithms is Low-Energy Adaptive Clustering Hierarchy (LEACH) [9]. With its cluster head election algorithm together with a cluster head rotation mechanism and data fusion within each cluster head, LEACH manages to reduce the energy dissipation by a factor of 7 when compared to direct communication and by a factor of 4 – 8 when compared to MTE [10].

Whilst there are advantages of using LEACH's distributed cluster formation algorithm, this protocol offers no guarantee on the placement and/or number of elected cluster head nodes. This may lead to inefficient setups which do not exploit the full potential of the algorithm posing a limit on the achievable network lifetime. In contrast, a centralised clustering system, such as LEACH-C [9], uses its global knowledge of the network to produce better clusters by dispersing the cluster head nodes throughout the network. During the cluster setup

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phase of LEACH-C, each node sends information about its current location (determined using a GPS receiver) and energy level to the base station. The energy level is used to ensure that the energy load is evenly distributed among all the nodes in the network whereas the location information provides for global knowledge of the network. The base station uses a simulated annealing algorithm to solve the NP-hard problem of finding *k* optimal clusters. This algorithm minimises the energy dissipation of the sensor nodes while transmitting their data to the cluster head by minimising the total sum of squared distances between all the non-cluster head nodes and the closest cluster head. This leads to an improvement in network lifetime of 62.5% (in terms of First Node Dies) when compared to LEACH [11]. Although centralised cluster-based algorithms tend to yield a better performance when compared to their distributed counterparts, this improvement comes at the expense of having sensor nodes equipped with extra hardware and a high energy cost network initialization phase.

In order to find a good compromise between these two approaches, the authors in [12] have presented a SOM neural network-based clustering algorithm whereby the base station collects network topological information through a low energy cost network initialization phase. The reported SOM algorithm elects an optimal number of cluster heads which are well dispersed throughout the network, reducing the energy dissipation and improving energy balancing between the nodes. Results presented show that an improvement in network lifetime of around 57.2% (in terms of First Node Dies) is achieved when compared to LEACH [12].

Apart from reducing the transmission distance of each sensor node, it is also imperative to reduce the amount of transmitted information. This is typically achieved through in-network processing whereby cluster heads aggregate data from multiple sensors to eliminate redundant transmission at intermediate nodes and provide fused information to the base station. In [13], the authors present a comprehensive survey of data aggregation techniques used in wireless sensor networks and compare various algorithms on the basis of performance measures, such as lifetime, latency and data accuracy. Although a lot of research has been carried out, there is still considerable communication overhead, between the measuring nodes and the aggregating node. For example, habitat temperature measurements are often predictable or do not change at all over a short period of time, this results in a lot of redundant data transfer reporting insignificant information to the aggregation node. Predictive filtering can be applied to exploit the fact that measurements from sensor nodes are fairly well predictable in order to reduce redundant data transfers, thus saving energy [14]. A highly promising solution is to apply the dual prediction scheme described in [14].

The choice of the prediction technique strictly depends on the nature of the data stream. In [14], the authors consider linear extrapolation, double exponential smoothing, and artificial neural network based predictors whereas the work in [15] is based on the use of Kalman filters. Although Kalman filtering was proven to be a successful technique, its practical application is limited as it requires a-priori knowledge about the statistical properties of both the phenomenon being observed and the measurement noise. An alternative solution, based on classic adaptive filter theory was presented in [16]. Here, the least mean square (LMS) algorithm was used to implement the dual prediction scheme described in [14]. The LMS-based data reduction strategy was tested on real world data collected by Mica2Dot sensor nodes [17] deployed in the Intel Berkeley Research lab [18]. Considering a temperature accuracy of ±0.5°C, the LMS-based data reduction strategy achieved a 90% reduction in transmissions.

III. RADIO AND ENERGY MODEL

The standard radio model used in wireless sensor networks uses both the Friss free space model and the multi-path fading model depending on the distance between the transmitter and receiver. If this distance is smaller than the crossover distance, $d_{crossover}$ [9], the transmit power is attenuated according to the Friss free space equation as follows [19]:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{1}$$

where $P_r(d)$ is the received power at a receiver distance of d metres, P_t is the transmit power, G_t and G_r are the gain of the transmitting antenna and receiving antenna respectively and λ is the wavelength of the carrier signal in metres.

Conversely, when the receiver distance is greater than $d_{crossover}$, the transmit power is attenuated according to the two-ray ground propagation equation [9]:

$$P_r(d) = \frac{P_t G_t G_r h_t^2 h_r^2}{d^4} \tag{2}$$

where h_t and h_r are the height of the transmitting and receiving antenna above ground level in metres respectively.

This standard energy model used in wireless sensor networks was proposed in [9]. Power control is used to invert this loss by adjusting the power amplifier to ensure that a certain power level is captured at the receiver [9]. Thus to transmit an *l*-bit message a distance d, the radio expends:

$$E_{TX}(l,d) = \begin{cases} lE_{Elec}(l) + l\varepsilon_{fs} d^2 & ; d < d_{crossover} \\ lE_{Elec}(l) + l\varepsilon_{mp} d^4 & ; d \geq d_{crossover} \end{cases} \tag{3}$$

To receive this message, the radio expends:

$$E_{RX}(l) = lE_{Elec}(l) \tag{4}$$

where, ε_{fs} and ε_{mp} are parameters which depend on the receiver sensitivity and noise figure and E_{Elec} is the electronics energy which depends on factors such as digital coding, modulation, and filtering of the signal [9].

IV. NACHO ALGORITHM

The general operation of the NACHO algorithm is based on the work presented in [12] whereby sensor nodes collect network topological information, through localized interactions, which is then transferred to the base station during the network initialization phase. As opposed to other centralised algorithms such as LEACH-C, the initialization phase allows the base station to have updated network topology awareness without the use of GPS-enabled sensors and without high energy cost procedures. The collected information is then used in conjunction with a Fuzzy-ART neural network-based algorithm at the base station to elect K_{opt} optimal cluster head nodes. In turn the cluster heads organize their clusters in a distributed approach.

The NACHO algorithm is divided into three phases and implements a cluster head rotation mechanism. Similar to LEACH, the operation of the algorithm is divided into rounds. Each round begins with a cluster setup phase, during which the clusters are organized, followed by a data transmission phase, throughout which data is transferred from the nodes to the cluster head. Each cluster head compresses the data from all the nodes within its cluster and relays the compressed data to the base station for further processing.

A. Initialization

During the initialization phase, the base station calculates important network parameters such as the optimal number of cluster heads, K_{opt}, and the minimum separation distance, R_{sep}, as discussed in [20]. Furthermore, the base station transmits a "Network Initialization" message to all the nodes in the network containing the value of R_{sep}. This signal is used by the nodes to calculate their distance from the base station, D_{ToBS}, by considering the received signal strength (RSS) as a distance metric, and use R_{sep} to engage in a "Local Neighbourhood Search" procedure to find the neighbouring nodes as described in [12]. Each node then transmits the list of neighbours together with its value of D_{ToBS} to the base station which in turn calculates and stores each node's centrality, concentration and D_{ToBS} as in [21]. This allows the base station to have network topology awareness. Furthermore, this phase was designed to have a very low energy cost by keeping the number of transmissions low and using small control packets.

B. Cluster Setup Phase

During the cluster setup phase, the base station elects K_{opt} cluster heads based on four parameters namely:

- *Node Residual Energy:* Elected nodes must have a high residual energy because cluster heads are involved in high energy consumption operations.
- *Centrality:* The node centrality defines the node's importance based on how central the node is to the cluster. A low centrality value is desired.
- *Concentration:* This defines the number of nodes present in the vicinity. A high node concentration ensures that cluster heads are placed where needed.
- *Cluster head (CH) frequency:* A record of the number of times each node served as cluster head is kept to avoid electing the same nodes repeatedly.

The election of the cluster heads in NACHO is carried out using a Fuzzy-ART neural network [22]. The algorithm ensures that the elected cluster heads have high residual energy, low centrality, high concentration and low cluster head frequency. The operation of the cluster setup phase is:

1. During the initialization phase, the base station collects all the information sent by the nodes and compiles a table similar to Table I. Note that the initial energy of each node is predefined and the cluster head frequency is set to 0. This table is updated during the operation of the network.

Node ID	**Centrality**	**Concentration**	**Energy**	**CH Frequency**	**Distance to BS**	**Neighbours**
1	0.34	3	0.5	0	80.5	4,9,5
2	0.53	2	0.5	0	75.2	6,56
…	**…**	**…**	**…**	**…**	**…**	**…**

TABLE I: INFORMATION COLLECTED BY THE BASE STATION

2. The Centrality, Concentration, Energy, and CH frequency for all the nodes whose status is set to 'alive' are extracted from the table, normalized and applied to the Fuzzy-ART neural network to cluster the nodes according to their cluster head quality. This is followed by the filtering algorithm yielding K_{opt} high quality cluster heads separated by R_{sep} as shown in Figure 1.
3. The base station informs the selected cluster head nodes for the current round and includes the above mentioned cost function parameters.
4. The selected cluster heads broadcast an "Advert CH" message to all the nodes in the network at a fixed power $P_{Broadcast}$ [20] including their Node ID, cost function parameters and residual energy level.
5. Nodes in the network receive the "Advert CH" messages and compute the cost for each cluster head. Two cost functions were considered:

Standard cost function based on received signal strength – In most algorithms, nodes choose the cluster heads based on the RSS to lower their energy consumption. However, as discussed in [23], this approach may lead cluster head nodes to exhaust their energy rapidly during data transmission since nodes which are further away from the base station have higher energy consumption.

Cost function based on a weighted distance-energy metric – To correct this problem we introduce a novel cost function based on a weighted distance-energy metric. By using the cost function given in (5), the nodes which are far away from the base station have a relatively high cost when compared to nodes which are in the vicinity of the base station. This cost value is further optimised by considering the residual energy of the cluster head in relation to that of the node. Thus although far away cluster heads incur a high cost, this value is lowered by an *energy offset.*

$$Cost(j,i) = w_1 * f\left(d\left(P_j, CH_i\right)\right) + \left(1-w_1\right) * g\left(d\left(CH_i, BS\right)\right) - \left(1-w_2\right) * \frac{E_{CH}}{E_{Node}} \quad (5)$$

$$f = \frac{d\left(P_j, CH_i\right)}{d_{f\_max}}; g = \frac{d\left(CH_i, BS\right) - d_{g\_min}}{d_{g\_max} - d_{g\_min}}$$

where $d(P_j, CH_i)$ is the distance between node P_j and cluster head CH_i, $d(CH_i, BS)$ is the distance between cluster head CH_i and the base station BS, w_1 and w_2 are the distance and energy weights respectively, d_{g_min} and d_{g_max} are distance parameters, $d_{f\_max} = Ex[max\{d(P_j, CH_i)\}]$, and E_{CH} and E_{node} are the cluster head and node residual energy respectively.

6. Each node selects the cluster head which has the minimum cost and sends a "Join Request" message to the selected cluster head node including its Node ID.
7. Cluster heads receive the "Join Request" messages.
8. Cluster heads notify the nodes of their acceptance.

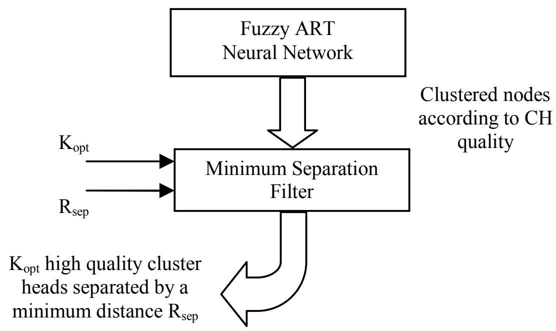

Figure 1: Cluster head election mechanism

C. *Data Transmission Phase and Cluster Head Rotation Mechanism*

During the data transmission phase, the nodes perform measurements and append status and residual energy information to each packet before transmitting it to their cluster head. The cluster heads receive this data, append their status and residual energy information, compress it and forward the resulting packet to the base station. This allows the base station to update the energy level and status of all the nodes in the network. Whenever the base station detects that a cluster head is 'dead', it broadcasts a re-cluster message to the whole network forcing all the nodes in the network to disassociate themselves from their current cluster head. As there is a cost in terms of time and energy associated with the cluster setup phase, the data transmission phase should be long when compared to this phase to reduce the effect of the overhead incurred during cluster formation on the overall performance. On the other hand, as the energy at each node is limited, running the data transmission phase for too long will drain the energy of the cluster head node and curtail communication between the non-cluster head nodes that have energy and the base station. For this reason, a cluster head rotation mechanism is employed to balance energy between the nodes. In NACHO, a cluster head rotation is triggered when the cluster head residual energy in the current round falls below the residual energy in the previous round by some percentage hysteresis. On a cluster setup phase re-start, the base station has an updated status of the network and re-calculates the optimal number of cluster heads K_{opt} to ensure optimality throughout the lifetime of the network. All these energy overheads related to the initialisation phase, cluster setup phase, associated re-clustering procedures and the appending of status/residual energy to the transmitted packets were considered in the simulations.

V. PREDICTION FILTERING ALGORITHM

The dual prediction scheme described in [14] requires a predictor in each node hence increasing the computational load and cost of the sensor node. This energy cost can be overcome by using the base station centric modified LMS predictive filtering scheme shown in Figure 2. This solution eliminates the predictor in the wireless sensor node but requires a low level signalling system for the base station to instruct the nodes to transmit their data when required.

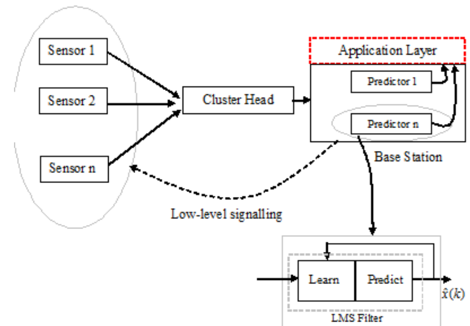

Figure 2: Base station centric predictive filtering scheme

The operation of the predictive filtering algorithm is shown in Figure 3. The sensor nodes initially enter the initialization phase during which they collect and report measurements to the base station via the cluster head. The base station uses this data to compute an estimate for the step size μ to be used in the filter weight adaptation process. Following this phase the base station starts computing predictions and operates in the training, prediction or sample check mode.

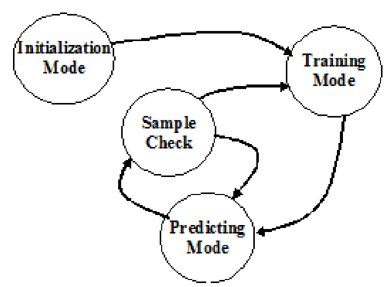

Figure 3: Base station centric predictive filtering algorithm state diagram

In training mode, the node transmits its recordings via the cluster head and the base station uses the last N measurements to compute a prediction for the upcoming measurement. Furthermore, the base station updates the set of filter coefficients w on the basis of the actual prediction error. As long as this error exceeds the error budget $|E_{max}|$, the sensor node operates in training mode. When this error falls below $|E_{max}|$ for R consecutive readings, the base station instructs the sesnor node to stop transmitting and sets the prediction period Q to its lowest value (Q=10). In prediction mode, the base station predicts the sensor measurements. At the end of period Q, the sensor node enters the sample check period during which it transmits N samples such that the base station checks whether the predictions are still within $|E_{max}|$. If the average error E_{avg} exceeds $|E_{max}|$, the base station instructs the sensor node to restart the training period and sets Q to its lowest value. Otherwise, the base station instructs the node to set Q

as shown in (6) and continues predicting measurements until another sample check period is reached.

$$Q=\begin{cases}100 & \text{if} \quad 0<E_{avg}\le 0.2*E_{\max} \\ 80 & \text{if} \quad 0.2*E_{\max}<E_{avg}\le 0.4*E_{\max} \\ 60 & \text{if} \quad 0.4*E_{\max}<E_{avg}\le 0.6*E_{\max} \\ 40 & \text{if} \quad 0.6*E_{\max}<E_{avg}\le 0.8*E_{\max} \\ 20 & \text{if} \quad 0.8*E_{\max}<E_{avg}\le E_{\max}\end{cases} \tag{6}$$

To minimise further the computational load, the predictor used is based on the modified clipped LMS algorithm [24] which significantly lowers the number of computations.

VI. Testing and Results

The NACHO algorithm and the predictive filtering algorithm were tested in a wireless sensor network simulator implemented in MATLAB®. Simulations were performed on 100 nodes uniformly dispersed in a 100m by 100m field with the base station located at coordinates (150m, 50m). The assumptions taken and energy parameters are tabulated in Table II and Table III respectively.

1	All sensor nodes and the base station are stationary after deployment and nodes cannot be added nor removed during the lifetime of the network.
2	The base station has an infinite energy.
3	The intra-cluster communication is based on the single-hop mode of operation.
4	Communication is symmetric and a sensor can compute the approximate distance on the RSS.
5	Network is homogeneous.
6	All sensors are location-unaware.

Table II: Assumptions Taken

Initial battery energy	0.5 Joules
Energy model parameter, ε_{fs}	$1*10^{-11}$
Energy model parameter, ε_{mp}	$1.3*10^{-15}$
Electronics Energy, E_{Elec}	50nJ/bit
Data packet length	4000 bits
Control packet length	200 bits

Table III: Energy Parameters

The performance of the NACHO algorithm was assessed along three metrics. These are (1) *First Node Dies (FND)* which defines the time taken for the first node to die, (2) *Half Nodes Alive (HNA)* which defines when half the network has died, and (3) *Transmitted Packets (TP)* which gives the total number of transmitted packets by the sensor nodes at FND.

To evaluate the validity and performance of the NACHO algorithm, simulations were carried out over 50 random networks. The mean and standard deviation values of the performance metrics were computed and compared to the results obtained through LEACH as shown in Table IV. These results show that the NACHO algorithm is capable of creating better clusters, increasing the energy balancing between the nodes whilst lowering the rate of energy dissipation. This in turn results in a significant improvement in the FND and HNA, leading to an increase in the number of packets received by the base station. Furthermore, the use of a cost function based on a weighted distance-energy metric (with w_1 and w_2 set to 0.9) further optimizes the energy dissipation and energy distribution between the nodes leading to an additional improvement in the network lifetime, with and increase of up to 79.6% in FND over LEACH as shown in Table IV, and a reduction in the FND to HNA transition time. A graphical representation comparing LEACH with NACHO is illustrated in Figure 4 while the superiority of the proposed NACHO algorithm with respect to other solutions is shown in Table V.

Metric	**NACHO Standard Cost function**		**NACHO with Proposed Cost Function**	
	Mean	Std.Dev	Mean	Std.Dev
FND	72.4%	3.5%	79.6%	3.2%
HNA	33.5%	1.1%	33.1%	1.3%
TP	43.9%	1.3%	51.1%	1.5%

Table IV: Performance Metrics Change

Algorithm	**Improvement over LEACH**
EEPSC [25]	45 %
LEACH-C [9]	62.5%
SOM-Clustering [12]	57%
NACHO	79.6%

Table V: Performance Improvement of Various Algorithms

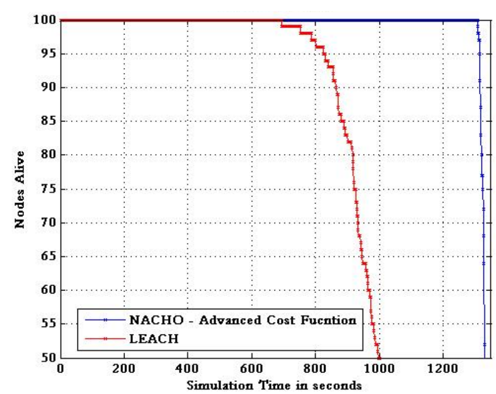

Figure 4: Network Lifetime

To evaluate the efficiency of the proposed predictive filtering algorithm, temperature data over a period of one month having a granularity period of one minute was obtained from the meteorological office of the Norwegian University of Tromso [26] and applied to the predictive filtering scheme described in Section V. Considering a maximum allowable error of 0.5°C, the ratio of the transmitted packets to the number of measurements was found to be around 11.5%. This is only slightly higher than that obtained using the standard dual prediction scheme described in [14] which amounts to around 6.75%. A plot of the output from the base station centric predictive filtering algorithm and the actual (raw) measurement data is shown in Figure 5.

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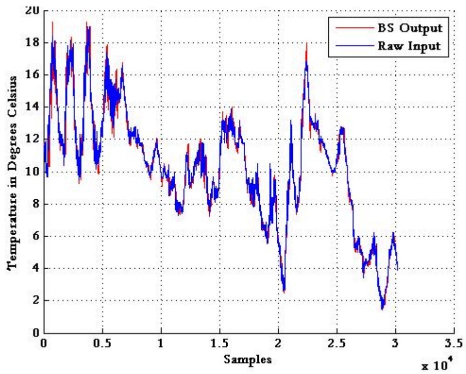

Figure 5: Comparison of proposed algorithm to the raw measurement data

By combining the base station centric predictive filtering algorithm with the NACHO algorithm, we achieve a significant improvement in the performance metrics over LEACH as shown in Table VI. This occurs because the number of transmitted packets is significantly reduced thereby drastically increasing the network lifetime whilst still monitoring accurately the environment. This result includes the energy dissipation due to all transmissions including the low level signalling required by the algorithm.

Metric	**NACHO with base station centric predictive filtering algorithm**	
	Mean	Std. Dev
FND / seconds	314%	3.6%
HNA / seconds	327.3%	1.8%
TP	369%	1.5%

TABLE VI: PERFORMANCE METRICS WITH PREDICTIVE FILTERING ALGORITHM

VII. CONCLUSION

In this paper, we have presented a cluster-based routing algorithm based on a Fuzzy-ART neural network and a novel cost function based on a weighted distance-energy metric. Simulation results have shown the efficacy of the algorithm as it manages to improve the system's lifetime by 79.6% when compared to LEACH. This represents an improvement of 17.1% and 22.4% when compared to LEACH-C [9] and SOM neural network-based clustering algorithm [12] respectively. Furthermore, by optimizing the distribution of energy between the nodes a reduced FND to HNA transition time was achieved hence improving the quality of the network. Predictive filtering was also applied at the base station to keep sensor node resources low. The proposed solution results in a significant increase in network lifetime while still providing accurate environment monitoring.

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