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Gaussian Regression Models for Evaluation of Network Lifetime and Cluster-Head Selection in Wireless Sensor Devices

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ABSTRACT The paper presents a model predictive approach for evaluating network lifetime and cluster head selection for a wireless sensor network. The dynamic parameters of a wireless sensor network are collected using Smart Mesh IP Power and performance calculator. The study considers a machine learning approach to combine clustering with the optimal routing protocol. The hop depth, advertising, number of Motes, backbone, routing, reporting interval, payload size, downstream frame size, supply voltage, and path stability are the predictors, and the current consumption, data latency, and build time are the response variables to establish the models for estimating the power and performance of the network. The remaining energy in each node, distance from the base station, and data transmission rate are the predictors, and the priority of the cluster head is the response variable to establish models for achieving an optimal routing path in a wireless sensor network. The standard tree, Support Vector Machine, Ensemble, and Gaussian process regression models for lifetime estimation are analyzed in comparison with the Smart Mesh IP tool, and the models for cluster head selection are investigated in comparison with ANFIS based models. This novel approach concentrates on the effect of various dynamic parameters on network lifetime prediction.

INDEX TERMS Cluster heads, machine learning, network lifetime, smart mesh IP tool.

I. INTRODUCTION

With the advent of self-powered IoT devices, power optimization is required at the system level, circuit level, component selection, and physical implementation level while maintaining the device's size, cost, and flexibility. Extending the battery lifetime of IoT devices become important when sensors are deployed in locations not easily accessible/risky locations, and the replacement of batteries becomes difficult.

Different low power circuit techniques used for reducing power consumption include Dynamic Voltage and Frequency Scaling, Multi-threshold CMOS technology, clock gating, and hardware-software co-design [1]. Increasing sleep time by turning off unused modules can help save power at the system level [1], [2]. System-level power management techniques with multi-level design space can help tradeoffs between high performance, low cost, and low power requirements.

Wireless Sensor Networks (WSN) change dynamically, impacting network lifetime parameters and synchronization issues. Different network parameters that affect the dynamic behaviour of WSN nodes are localization, connectivity & coverage, anomaly detection, fault detection, routing, congestion control, medium access control, data aggregation, target tracking and quality of service, various synchronization issues, event detection, energy harvesting, and mobile sink [3]. Some of the challenges in WSN include finding an optimum path for dynamic networks in three-dimensional space, implementing effective protocols, and reducing packet collisions for the dynamic network to improve reliability in large-scale networks that adapts to dynamic changes by self-charging and discharging duty cycles.

Different network parameters include:

- Advertising rate - the rate at which motes in-network advertise.

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- Join duty cycle - how much time a searching mote spends listening for a network Vs. sleeping
- Downstream bandwidth - affects how quickly motes can send data
- Number of motes - contention among many motes simultaneously trying to join for limited resources slows down joining with collisions
- Mote join state machine timeouts and path stability – user has little or no control.
- Network topology – Mesh networks are self-healing, while star and tree networks have a single point of failure.
- Recovery time – if one of the nodes is powered down, time taken by the network to re-establish the full mesh or recover all other nodes for uninterrupted data delivery without degradation in the Quality of Service (QoS) metric.

The Internet of Things (IoT) connects devices to the internet via the IP protocol. Low energy consumption and low power operation become critical for IoT devices as they operate on batteries or harvest energy from the environment. Predicting the energy consumption and the device lifetime is thus essential for selecting the most suitable technology, communication protocols and finding the optimal configuration parameters in a network.

A. BACKGROUND STUDY AND LITERATURE SURVEY

The operating temperature and discharge current values influence energy stored in battery devices. Software and hardware-based approaches are used to estimate the state of charge and voltage of batteries using analytical battery models and electrochemical cells to implement energy-aware policies. In literature, studies have evaluated the cost of complex algorithms in terms of memory usage, power consumption, and execution time in low-power MCUs. The cyclical behaviour of WSN nodes is assumed, and an open-loop computation is used to study the behaviour of the battery [4].

Routing protocols choose the correct route from cluster head to base station. The objective of routing is to realize the scalability of the network, improve the data transfer and energy efficiency of WSNs. Energy-efficient routing protocols are classified based on network structure, communication model, topology, and reliable routing. Based on the network structure, routing protocols are classified as flat, hierarchical, and location-based protocols. In flat network architecture protocols like Sensor Protocol for Information via Negotiation (SPIN), Directed Diffusion, and Rumor Routing, the nodes follow a standard rule for data transmission. In hierarchical networks, the Cluster Heads (CHs) are responsible for communicating with the Base station. Each node is equipped with GPS in location-based networks, and sleep mode schemes are incorporated. Geographic Adaptive Fidelity (GAF), Geographic and Energy Aware Routing (GEAR), and SPAN are routing protocols based on location.

Clustering is a solution used to solve network partitioning that arises because of the limited capacity of battery nodes [5]. Low Energy Adaptive Clustering Hierarchy (LEACH) is the most famous hierarchical routing protocol, where the cluster head (CH) is selected on a rotation basis based on a probabilistic threshold value, and only CHs are allowed to send the information to the base station (BS). Some of the drawbacks of LEACH include improper distribution of energy, non-reflection of remaining energy in nodes and unidentified CHs after some iteration.

LEACH (Low Energy Adaptive Clustering Hierarchy) was proposed to guarantee a balanced energy utilization and to enhance the efficiency of WSNs by partitioning the network into multiple clusters and through a random Cluster Head (CH) rotation [6]. LEACH is a Medium Access Control (MAC) protocol based on the Time Division Multiple Access (TDMA) method. Two main stages of the LEACH algorithm include the Setup phase and Data Transfer Phase. The setup phase includes Cluster selection, TDMA schedule creation, and Cluster configuration. In the setup phase, a sensor node becomes a Cluster head if the number is less than the threshold value defined by eq (1):

$$T(n) = \left\{ \begin{array}{ll} \dfrac{P_L}{1 - P_L * (r \; mod \frac{1}{P_L})} & n \in C \\ 0 & Otherwise \end{array} \right\} \quad (1)$$

where P_L introduces the percentages of CHs in each epoch, r is the present epoch, and C is a set of sensor nodes that have not yet been CH in the period $1/P_L$ epoch. Once CHs are chosen, the nodes join the cluster heads depending on specific metrics to the cluster head. The different metrics based on which CHs may be selected are (1) residual energy, (2) Centralization, (3) mobility, (4) energy efficiency, and (5) distance. Once clusters are established, the CHs send a TDMA schedule to allow nodes to recognize their time slot for sending the data to CHs. After the fusion of data by CHs, these data will be forwarded to the sink using the Code Division Multiple Access (CDMA) code to avoid collision [7]. The data transfer stage routes the data to the base station either using single-hop or multi-hop techniques. The advantage of LEACH is that the nodes remain in sleep mode until their turn to send data. The disadvantage of LEACH is that for a random selection of CHs the number of cluster heads cannot be guaranteed in each round. Also, as the remaining energy in each node is not considered, the nodes with low residual energy and high residual energy have the same chance of becoming cluster heads. CHs use the single-hop to direct data to the BS, making LEACH not adopted for an extensive network. Different authors [8], [9] have surveyed various descendants of LEACH protocol like LEACH-C, MM-LEACH, TL-LEACH, Stable Election Protocol (SEP), V-LEACH, and Modified (MOD-LEACH). Table 1 shows the performance of various LEACH algorithms in terms of the number of data packets delivered to the Base station (BS), first dead node, and total energy dissipated.

TABLE 1. Performance of various LEACH algorithms [10], [11].

Performance metrics	*LEACH*	*LEACH-C*	*LEACH-GA*	*LEACH-PSO*	*Fuzzy based LEACH*
No of data packets delivered to BS	4810	4890		6810	11110
First dead node	348 round	379 round	696 round	398 round	410 round
Total energy dissipated (J)	2030	1962			

In LEACH-B, there is a Uniform Number of CHs given by the global number of nodes in the network and the proportion of CHs. The algorithm considers remaining energy after the first round and shows improvement in network lifespan than LEACH.

Intelligent (I-LEACH) elects CH based on the remaining energy and nodes location. However, CH integrates collected data to reduce the cost of supplementary data transmission, which is not practical for nodes that receive different data.

The residual energy of nodes E_r

$$E_r = \frac{E_{current}}{E_{max}} \tag{2}$$

where E_{max} presents the initial energy of the node, while $E_{current}$ represents the residual energy of each node.

The distance from the base station to CH is given by

$$d_{bs-CH} = \frac{d_{bs}}{d_{far}} \tag{3}$$

Here, d_{bs} parameter denotes the distance between a node and the BS, when the distance from the farthest node in a cluster to the BS is expressed by d_{far}. To extend the network lifetime and the scalability, functions described in Eqs. (2) and (3) are incorporated and multiplied by the probability function.

The LEACH protocol uses the energy model as used in Heinzelman *et al.* [12]. Energy consumption at each node depends on the size of the data packet and the distance from the source node. For transmitting the l- bits of a data packet from a sensor node to its d distance remote receiver node, the total energy consumption of a sensor node is calculated by the following equation:

$$E_{Tx}(l, d) = \begin{Bmatrix} l * E_{elec} + l * \epsilon_{fs} * d_2 & if\ d < d_0 \\ l * E_{elec} + l * \epsilon_{mp} * d_4 & if\ d \geq d_0 \end{Bmatrix} \tag{4}$$

However, for receiving the l-bits of a data packet at a sensor node, the energy consumed by the receiver nodes is calculated by the following equation:

$$E_{Rx} = l \times E_{elec} \tag{5}$$

The value of the E_{elec} is the energy dissipated per bit during the execution of the transmitter or receiver circuit. ϵ_{fs} and ϵ_{mp} is the amplification coefficient of the transmission amplifier for free space and multi-path model, respectively. d_0 represents threshold transmission distance, and its value is generally

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}. \tag{6}$$

1) FINDING THE OPTIMAL NUMBER OF CLUSTER HEADS K

For N sensors divided into C clusters, the energy consumption of the cluster head is given by

$$E_{CH} = kE_{elec}\frac{N}{C} + KE_{DA}\frac{N}{C} + K\epsilon_{mp}d^4_{toBS} \tag{7}$$

where E_{DA} is the energy consumed in aggregation d_{toBS} is the average distance from the base station to the cluster head nodes.

Energy consumed in non-cluster head nodes for transmitting the packet to the cluster head is given by

$$E_{Non-CH} = kE_{elec} + KE_{DA}\frac{N}{C} + K\epsilon_{fs}d^2_{toCH} \tag{8}$$

$d^2_{toCH} = \frac{M^2}{2\pi C}$ is the average distance from the non-cluster head nodes to their cluster head nodes. R is the radius of the network and $\frac{M^2}{C}$ is the area of each cluster.

Total energy dissipated by a cluster is given by

$$E_{cluster} = E_{CH} + E_{Non-CH}\frac{N}{C} \tag{9}$$

Total energy dissipated for the frame is:

$$E_{total} = CE_{cluster} \tag{10}$$

The optimal cluster heads can be obtained by differentiating E_{total} with respect to C

$$k_{optimal} = \frac{\sqrt{N * \varepsilon_{fs}}}{\sqrt{2\pi}}\frac{1}{\varepsilon_{mp}}\frac{M}{d^2_{toBS}} \tag{11}$$

Elshrkawey *et al.* [13] has discussed an enhanced schedule based on Time Division Multiple Access (TDMA) and augmentation of energy balancing in clusters among all sensor nodes to reduce energy consumption and prolong the network lifetime of WSN. A sensor node is considered a cluster head if the random number of the sensor node is less than the threshold value defined using factors like remaining energy of the sensor node, the distance of sensor node to the base station, and the number of times a node is selected as a cluster head.

SEP (Stable Election Protocol) [14] can be applied for heterogeneous networks where a fraction of m nodes have additional energy factor α. The probability of these advanced nodes to become CHs is given by

$$p_{adv} = \frac{p_{opt}(1+\alpha)}{1+m\alpha} \tag{12}$$

An increase in the number of advanced nodes results in an increased stability period and network life. However, throughput is also increased due to two levels of heterogeneity.

TEEN [15] has two threshold levels - a hard threshold and a soft threshold. Nodes turn on their transmitters whenever the sensed attribute's value becomes equal or greater than the hard threshold, and data is conveyed to CHs. And for the second time, they transmit only in case the difference between sensed value and previously saved value at which transmission was done is greater than or equal to soft threshold. So, energy consumption and throughput are reduced; hence network life and stability period are improved than other protocols.

Sharma S *et al.* [16], have used residual energy as a factor to make cluster head. The radial-based function network model and Artificial Neural Network (ANN) are used for the cluster head selection problem. The improved performance is observed in the number of alive nodes, total energy consumption, cluster head formation, and the number of packets transferred to the base station and cluster head compared with LEACH and LEACH-C algorithms.

Han *et al.* [17] have discussed Clustering protocol based on the meta-heuristic approach (CPMA) that focuses on cluster head selection based on Harmony Search Algorithm, which aims to reduce total energy dissipation. The CPMA uses the Artificial Bee Colony algorithm to optimize crucial parameters.

Seyyedabbasi *et al.* [18], have developed an algorithm HEEL where the cluster head is selected based on node energy, the energy of node's neighbour, number of hops, and number of links to neighbours and shows improvement compared to Nr-LEACH, ModLEACH, LEACH-B, LEACH, PEGASIS energy-aware clustering scheme.

Aslam *et al.* [19] proposed a novel method for integrating a multi-objective function for charging a wireless portable charging device and sensor node's training for data routing carried out using clustering and reinforcement learning. The techniques used in our paper SVM and KNN have only been proposed as future scope of research and have not been implemented in lifetime prediction or selection of cluster heads.

Different performance metrics of clustering algorithm include:

i. Total Energy Consumption (E_{total}) - It is defined as total energy consumption in the network after k rounds of data gathering from the area of interest.

$$E_{total} = \sum\nolimits_{i=1}^{N} E_{i,k} \tag{13}$$

Here $E_{i,k}$ is the total energy consumption by a node i after k number of rounds of data gathering from the network. N is the total number of nodes in the network.

ii. Number of alive nodes (N_{alive_nodes}, k): It is defined as the total number of nodes alive whose residual energy is greater than the threshold energy after a specified number of data gathering rounds (k).

$$\left(N_{alive_{nodes}}, k\right) = |N_i|\,; \quad 1 \leq i < N \text{ and } E_{residual_i} > E_{threshold} \tag{14}$$

iii. Network lifetime: It is defined as the number of data gathering rounds that a WSN has carried on until the first node death.

A comparison of energy consumed by different wireless protocols like IEEE 802.15.4/e, Bluetooth low energy (BLE), the IEEE 802.11 power-saving mode, the IEEE 802.11ah, LoRa and SIGFOX is carried out based on the power required in the sleep mode, idle mode, transmit and receive mode and the duration of each state using an analyzer [20]. The results showed that BLE obtained the best network lifetime in all traffic intensities. At ultra-low traffic intensities, LoRa obtained the third-best network lifetime.

In literature [21]–[28] the energy consumption models take transmission power, the distance between two nodes, packet size, and path loss as parameters to predict battery lifetime. The approach modelled the behaviour of the physical layer, and it did not reflect the operation of duty-cycled IoT devices realistically. The topology of all networks considered in these works is the star.

The importance of Machine Learning (ML) in WSNs due to the dynamic nature of networks is presented [29]. Maddikunta *et al.*, [30] have predicted battery life based on various regression models, and predictive accuracy of 97% was obtained. The different predictors used in work include the beach name, water temperature, turbidity, transducer depth, water height, wave period, and measurement timestamp.

Artificial Intelligence is unlocking software solutions like ML approaches in battery systems to reduce fabrication and development costs while improving performance metrics. Data-driven models with ML algorithms can be used to predict the state of charge and remaining useful life in batteries. ML techniques can be applied to dynamic wireless sensor networks to affect the adaptiveness and ability of networks to respond quickly and efficiently without compromising the quality of service.

Support Vector Machine (SVM) is a non-parametric method that relies on kernel functions to perform classification and regression tasks [31]. Here, a Lagrangian function is constructed as an objective function, and by introducing α_n and α_n^* (non-negative multipliers) for each training data x_n and response y_n.

$$\begin{aligned} L(\alpha) = &\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) G\left(x_i, x_j\right) \\ &+\epsilon\sum_{i=i}^{N}\left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{N} y_i\left(\alpha_i^* - \alpha_i\right) \end{aligned} \tag{15}$$

where the Gram matrix $G(x_i, x_j)$ represents whether the kernel function is linear, polynomial or gaussian.

Subject to the constraint

$$\sum_{n=1}^{N}\left(\alpha_n-\alpha_n^*\right)=0 \tag{16}$$

$$\forall n\colon 0 \leq a_n, \alpha_n^* \leq C \tag{17}$$

where C is the box constraint that controls the penalty imposed on data points that lie outside ϵ margin and prevents the problem of overfitting.

The function used to predict new values is given by

$$f(x)=\sum_{n=1}^{N}\left(\alpha_n-\alpha_n^*\right)G\left(x_n,x\right)+b \tag{18}$$

Each Lagrange multiplier is updated with each iteration until the convergence criterion is met.

Ensemble learning is an ML and statistical technique that uses different ML algorithms to improve predictive performance. Here a Least Square Boosting (LSBoost) method minimizes the mean squared errors.

Gaussian Process Regression (GPR) is a probabilistic and non-parametric model [32].

For a training set $\{x_i, y_i\}$ the GPR model is given by

$$P(y \mid f, X) \sim N\left(y \mid H\beta + f, \sigma^2 I\right) \tag{19}$$

where f represents a Gaussian process with zero mean for each input x_i, H represents the set of basis functions that projects the inputs into feature space, β basis function coefficients and σ^2 error variance. While training using a GPR model, the coefficient of basis function, the noise variance σ^2 and hyperparameters of the kernel function are estimated.

The selection of an appropriate ML model is insufficient for obtaining excellent performance and tuning the model argument before the learning process is called hyper-parameter tuning. Bayesian optimization is an effective hyperparameter optimization tool.

One of the major issues encountered in machine learning models is the problem of the bias-variance dichotomy. Bias is the error that is introduced by the model's prediction and the actual data.

$$\text{Bias} = \text{Predicted–Actual} \tag{20}$$

High Bias means the model has created a function that fails to understand the relationship between input and output data. Low Bias means the model has made a function that has understood the relationship between input and output data.

Variance - is the amount by which its performance varies with different data set.

Low variance means the machine learning model's performance does not vary much with the different data sets. High variance means the machine learning model's performance varies considerably with other data set.

A well-trained model should have low variance, and low Bias is also known as Good Fit.

Overfitting - During the training phase, the model can learn the complexity of training data in so detail that it creates a complex function that can almost map entire input data with output data correctly, with very little or no error. The model shows low error or Bias during the training phase but fails to show similar accuracy with the test or unseen data (i.e., high variance)

Underfitting - During the training phase, the model may not learn the complex relationship between training data in detail and can come up with a straightforward model. It is so simple that it produces too much error in prediction (high Bias).

RMSE of training data should be more or less the same as the RMSE of testing data. The techniques for reducing overfitting include increasing training data, reducing model complexity, early stopping during the training phase, L1 and L2 regularization, and dropouts for the neural network. Techniques for reducing underfitting include increasing training, increasing model complexity, increasing the number of features, removing noise from data, and increasing the number of training epochs.

Regularization is a technique that makes slight modifications to the learning algorithm such that the model generalizes in a better way. In L1 regularization, a penalty term that contains the absolute weights is added to reduce the complexity of the model. The equation for L1 regularization is given by:

$$L\left(x,y\right)=Min(\sum\nolimits_{i=1}^{n}\left(y_i-w_ix_i\right)^2+\lambda\sum\nolimits_{i=1}^{n}\left|w_i\right|) \tag{21}$$

In L2 regularization, a penalty term that contains lambda times squared weight of each feature is added to reduce the complexity of the model. The equation for ridge regression will be:

$$L\left(x,y\right)=Min(\sum\nolimits_{i=1}^{n}\left(y_i-w_ix_i\right)^2+\lambda\sum\nolimits_{i=1}^{n}\left(w_i\right)^2) \tag{22}$$

Due to the addition of this regularization term, the values of weight matrices decrease because it assumes that a neural network with smaller weight matrices leads to simpler models. Therefore, it also reduces overfitting to quite an extent.

The design of energy balanced and energy-efficient routing protocols is required for increasing the lifetime of wireless sensor nodes. Hierarchical clustering protocols extend the network lifetime by dividing nodes into multiple clusters. Some clustering algorithms in the literature are listed in Table 2.

B. CONTRIBUTION AND PAPER ORGANIZATION

In this paper, ML methods are used to i) predict the CHs and an optimum number of nodes in a network ii) forecast the energy consumed of IoT nodes by considering the dynamic nature of the networks. The highlights of the paper include

- Dataset creation for prediction of current consumption, data latency and build time of Wireless Sensor Networks

TABLE 2. Literature survey on clustering algorithms.

Author Details	*Contributions*
Padmalaya Nayak, and D. Anurag [33]	A Mamdani fuzzy-based LEACH is proposed with inputs as remaining battery power, mobility of base station, and centrality of clusters. The results indicate that the first node survives double the time, has 62% reduced end-to-end delay, is more stable, and has 20% more life than LEACH.
J-Kim et al.[34]	CHEF, another fuzzy logic-based clustering approach, elects a node with high energy and locally optimal one as the cluster head (CH). The simulation result shows that the CHEF is 22.7% more efficient than LEACH. The three fuzzy input parameters considered in CHEF are energy, concentration, and centrality.
T Sharma and B. Kumar [35]	F-MCHEL is an improvement over CHEF that provides more network stability than LEACH and CHEF.
Mohit Mittal, Krishan Kumar [36]	A self-organization map neural network an unsupervised learning network is used in this work.
Zongshan Wang, Hongwei Ding, Bo Li, Liyong Bao, Zhijun Yang [37]	Here, clustering using an improved artificial bee colony is used for selecting the CHs. The simulation results show that the proposed algorithm has a good energy consumption balance, energy efficiency, network life, period of network stability, and throughput.
Yuan Zhou, Ning Wang and Wei Xiang [38]	An improved Particle Swarm Optimization (PSO) technique based on the location of the base station, area, and number of nodes is used to create the cluster structure to optimize the network's energy consumption and minimize the transmission distance.

- A model predictive approach for evaluating the network lifetime and cluster head selection in a Wireless Sensor Network
- Validation of the machine learning-based lifetime prediction model using Smart Mesh IP tool.

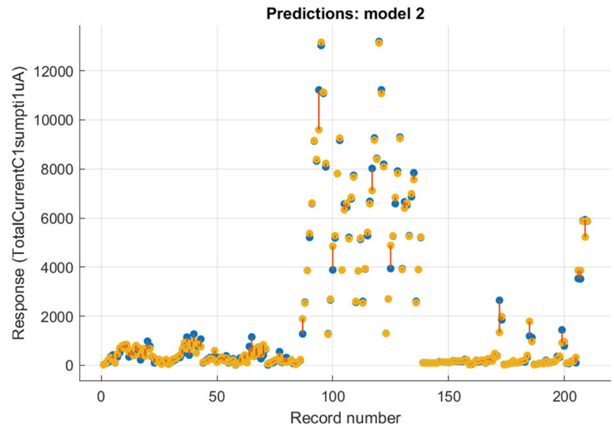


FIGURE 1. Dataset for lifetime prediction is developed using SmartMesh IP tool.

- Comparison of the machine learning-based cluster head selection model with ANFIS based models.
- Here considered analysis on the effect of various dynamic parameters on network lifetime prediction.
- Machine Learning based cluster head priority is combined with modified threshold sensitive Stable Election Protocol (TSEP) for cluster head selection.
- A comparison of various protocols like TEEN, SEP, LEACH and Machine Learning based TSEP (ML-TSEP) is carried out in terms of the average energy of each node and the number of dead nodes.
- This work contributes a novel approach to combining clustering with the optimal routing protocol.

The paper has been organized as follows: Section II describes the data-driven and model predictive approach for combining the clustering and routing protocol in Wireless Sensor Networks. The results for Lifetime prediction and cluster head selection using ML are presented in Section III. A comparison of different ML techniques with its performance metric is also carried out in this section. The concluding remarks are outlined in Section IV.

II. DATASET FOR THE MODEL PREDICTIVE WIRELESS SENSOR NETWORK

The dataset for lifetime prediction is developed using smart mesh IP tool [17] as shown in Fig. 1. A sensitivity study of various network parameters and its dependency on total current consumption of the network is also carried out using the data generated (Fig. 2-4).

III. MODEL PREDICTIVE APPROACH FOR OPTIMAL ROUTING PATH AND LIFETIME PREDICTION

A WSN consists of a network manager and several motes. The proper network interfaces configuration can address a wide range of sensor applications to tradeoff between speed and power consumption. Each mote represents a location where the sensor can send and receive data. The network manager builds and maintains the network and makes available the sensor data for data collection applications. Some motes can

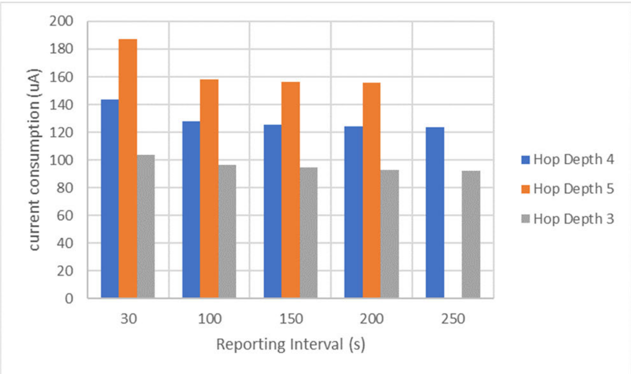


FIGURE 2. Variation of current consumption with reporting interval at different hop depth.

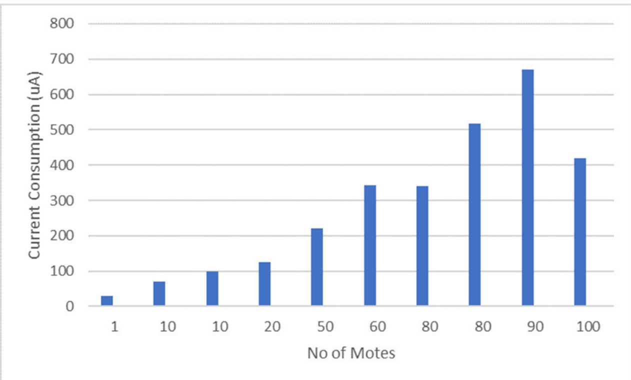


FIGURE 3. Variation of current consumption with No. of Motes.

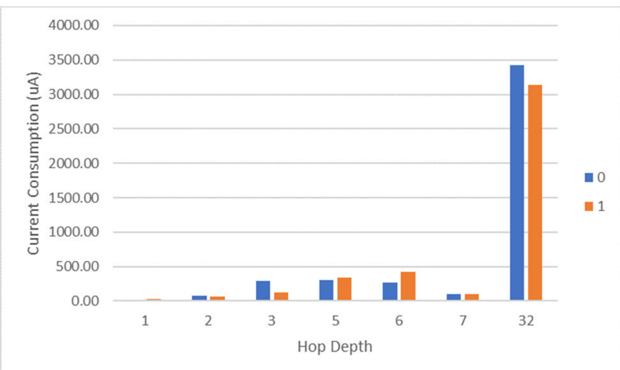


FIGURE 4. Variation of current consumption for different hop depths (0 – Routing, 1- Non-routing).

directly communicate to the manager, while others must route the data through other motes. Turning off-network advertising and reducing downstream communication can reduce the network's power consumption, thereby doubling the battery life of nodes. Configuring the nodes as a mesh network and configuring all battery-powered nodes to be non-routing can also result in a battery life greater than ten years. Non-routing nodes behave as leaf nodes that do not advertise and never route the data. Setting the backbone mode on at the manager reduces the data latency of the network; Fig. 5 shows a WSN obtained from the Smart IP Mesh calculator. Here we

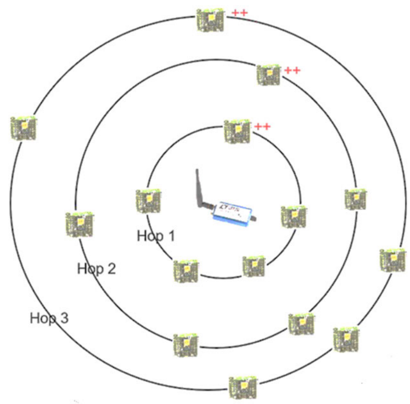


FIGURE 5. A network with 30 motes and 3-hops.

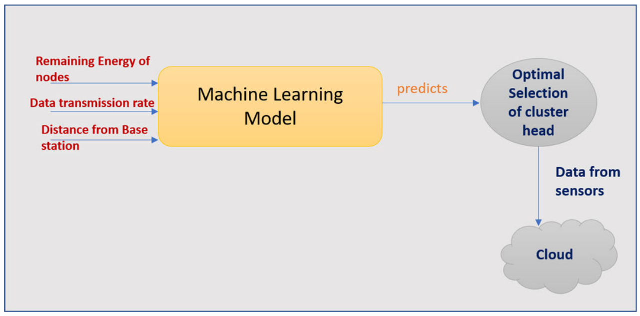


FIGURE 6. Block diagram for optimal routing path of the network.

consider a WSN consisting of 200 sensor nodes installed on one floor of a building. The network is divided into four occupancy zones, each with its own Passive Infrared [PIR], Occupancy Sensors, two LED Luminaires and motorized window blinds [39], [40].

The selection of CHs with appropriate clustering protocols is another crucial aspect for enhancing the network lifetime of IoT nodes. Optimal CHs are selected to obtain efficient routing in a multi-hop communication network. Fig. 6 shows the block diagram for the optimal routing path of the network. In work presented in [41], a Fuzzy based LEACH protocol was developed to obtain a priority value for the CH based on the initial energy, distance from the base station, and data transmission rate. Using the Fuzzy based LEACH, the input-output training dataset for ANFIS based LEACH is developed. The same dataset is used for training the machine learning model. The predictors of the Machine Learning model are the Remaining energy of nodes, Data Transmission rate, and distance from the base station. Various machine learning models like Gaussian Process Regression, Support Vector Machine, Ensemble, and Decision Tree are deployed using the dataset. The detailed pseudocode for cluster Head Priority using Gaussian Process Regression (GPR) with Bayesian Optimization is illustrated in Table 3. Once the optimal cluster heads are selected, those sensors transfer data to the cloud.

The power and performance predictor considers network topology, data report rates, packet size, supply voltage,

TABLE 3. Algorithm for gaussian process regression (GPR) with Bayesian optimization for cluster head priority.

Algorithm: Gaussian Process Regression (GPR) with Bayesian Optimization for cluster Head Priority
Input: Set of 100 sensor nodes, with known initial energy E_r, Data transmission rate r and distance from the base station d_{bs-CH}.
Output: Priority of node to become cluster head 'p'

Step 1: Deriving ANFIS based LEACH for cluster head priority

i. Load training data generated from fuzzy-based LEACH

p = evalfis(fis,[E_r; d_{bs-CH};r],options);

ii. Use the existing fuzzy structure and Back Propagation optimization techniques to train the model using the Neuro-fuzzy designer tool of MATLAB

Step 2: GPR with Bayesian optimization for lifetime prediction and cluster head priority

Initialization:

- Place a Gaussian process prior on f
- Observe f at $n0$ points according to an initial space-filling experimental design.
- Set n at $n0$

While $n \leq N$ do:

- Update the posterior probability distribution on f using all available data for cluster head priority and lifetime prediction.
- Identify the maximizer xn of the acquisition function **EI** over $\mathcal{X}$, where the acquisition function is calculated using the current posterior distribution $EI(x) = \mathbb{E}(\max(f(x) - f^*, 0))$ where f^* is the maximum value of f seen so far.
- Observe $yn = f(xn)$
- Increment n

End while

Return the point evaluated with the largest $f(x)$ or the point with the largest posterior mean.

and packet success rate as inputs and predicts the average current consumption, data latency, and network build time. Fig. 7 shows the block diagram for the network lifetime prediction model. The model used for predicting the current consumption, data latency, and build time of the WSN makes use of ten predictors, namely hop depth, advertising, number of motes, backbone, routing, reporting interval, payload size, downstream frame size, supply voltage, and path stability. Five-fold cross-validation is performed on the model to overcome the overfitting problem and to obtain a reasonable accuracy estimate on each fold. In k-fold cross-validation, the data is partitioned into k disjoint sets. Here the data is trained on the k-1 data set and tested first. The process is carried out for k iterations, and the accuracy score is calculated.

TABLE 4. Parameters used for simulation of LEACH, SEP, TEEN, and ML-TSEP.

Parameters	Values
Initial Energy E0	0.1 J
Optimal Election Probability of a node to become cluster head p_{opt}	0.2
Energy dissipated per bit during execution of the transmitter or receiver circuit Eelec	50nJ/bit
Amplification coefficient of the transmission amplifier for free space ϵ_{fs}	10pJ/bit
Amplification coefficient of the transmission amplifier for multi-path model Emp	13 pJ/bit
Data Aggregation Energy EDA	5 nJ/bit
Values for Heterogeneity Percentage of advanced nodes	m=0.5; alpha a=1;
Maximum number of rounds rmax	100

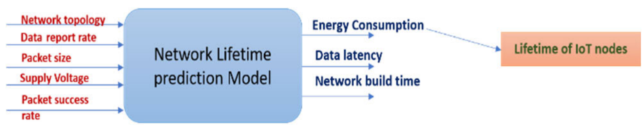


FIGURE 7. Network lifetime prediction model.

The developed model is used to evaluate the dependency of various parameters on power and performance.

A network consisting of 200 nodes is placed randomly in a region of 100 × 100 sq.m, and the Base station is placed in the center. The parameters used in MATLAB simulation are shown in Table 4

In the proposed Machine Learning-based Threshold Sensitive Stable Election Protocol (ML-TSEP), a node's probability to become CH is decided from the machine learning model. In TSEP, two levels of heterogeneity is considered, and the transmission of data from sensor node to CH takes place based on the threshold defined by

$$T_1(n) = T(n)\frac{E_{re}}{E_{in}}\left(1 - \frac{1}{E_{avg}}\right)\frac{d_{toBSav}}{d_{toBSn}}\left(1 - \log_{10} d\right) \times \frac{1}{CH_s} Nb_n \quad if\ n \in G \tag{23}$$

$T(n)$ is the threshold defined in LEACH algorithm
E_{re} is residual energy of sensor nodes
E_{in} is initial energy of sensor nodes
E_{avg} is the average energy of sensor nodes in current round
d_{toBSav} is average distance of sensor nodes to base station
d_{toBSn} is distance of sensor node to base station
CH_s is the time that node is selected as a cluster head
Nb_n is the number of neighbours of n nodes.
G is set of sensor nodes that have not been cluster heads

The summary of the steps involved in the proposed method include:

TABLE 5. RMSE and other performance metric for the lifetime prediction model.

Parameters	*Tree*	*SVM*	*Ensemble*	*GPR*
RMSE (uA)	584.79	705.55	459.65	233.85
R-squared	0.96	0.94	0.98	0.99
MAE (uA)	263.47	283.16	272.24	111.72
Prediction speed(obs/sec)	22000	19000	5500	21000
Training time (s)	26.723	149.3	114.52	142.28
Optimizer	Bayesian	Bayesian	Bayesian	Bayesian
Feature selection	No	No	No	No
PCA enabled	No	No	No	No

Data Gathering - For lifetime prediction, the data is collected from the SmartMesh IP tool, and for cluster head priority, the data is collected from the fuzzy-based model.

Data preprocessing to remove outliers and deleting duplicates

The features most affecting the lifetime are identified for the lifetime prediction model.

Build machine learning models using a Decision tree, Support Vector Machine, Ensemble, and Gaussian Process Regression

Analyze the performance metrics of the models and identify the best model

Hypertuning of the parameters using Bayesian optimizer

Validation of the lifetime prediction model using test data obtained from SmartMesh IP tool.

Comparison of the results (Mean Squared Values) of Machine Learning based and ANFIS based cluster head priority.

Machine Learning based cluster head priority is combined with modified Threshold Sensitive Stable Election Protocol (ML-TSEP) for cluster head selection. The threshold value of the modified TSEP is given by (23)

A comparison of various protocols like TEEN, SEP, LEACH Machine Learning based Threshold Sensitive Stable Election Protocol (ML-TSEP) is carried out in terms of the average energy of each node and the number of dead nodes.

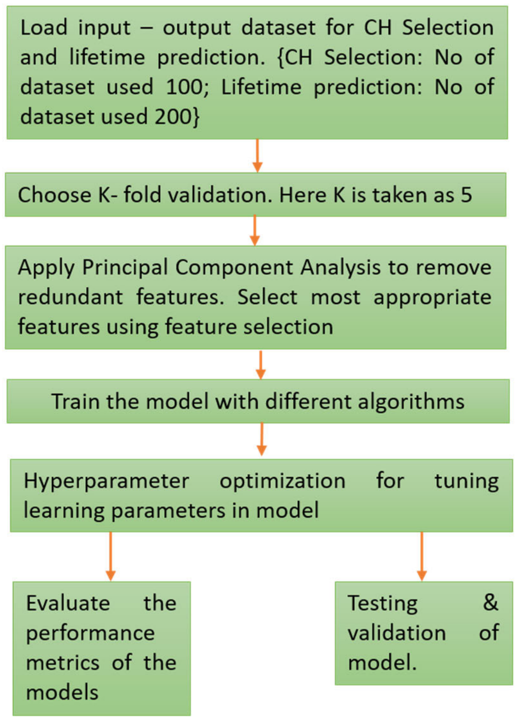


FIGURE 8. Flow Diagram for a model predictive based optimal routing and lifetime prediction.

IV. RESULTS

A. LIFETIME PREDICTION MODEL USING ML

The different steps involved in developing an ML model include data collection, data preprocessing, model development, training, hyperparameter optimization, testing and validation, as depicted in Fig. 8.

The different performance metrics used for evaluating the regression model include root mean squared error, R-squared, mean absolute error, prediction speed and training time.

Mean Absolute Error (MAE) is the sum of the average of the absolute difference between the predicted and actual values given by (24)

$$MAE = \frac{1}{n}\sum \left| Y_i - \hat{Y}_i \right| \tag{24}$$

where Y_i = actual output values, = $\hat{Y}_i$ predicted output values.

The mean squared error (MSE) is given by Eq.(24).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{25}$$

R-squared explains to what extent the variance of one variable explains the variance of the second variable. Higher the R-squared value, the better is the model.

As there is more than one independent variable, linear regression is not used for predictive analysis. Table 5 shows the RMSE and performance metric for the lifetime prediction model, and Fig. 9 shows the predicted and actual responses for different algorithms.

The models are validated against actual current consumption and predicted current consumption, as shown in Fig. 10.

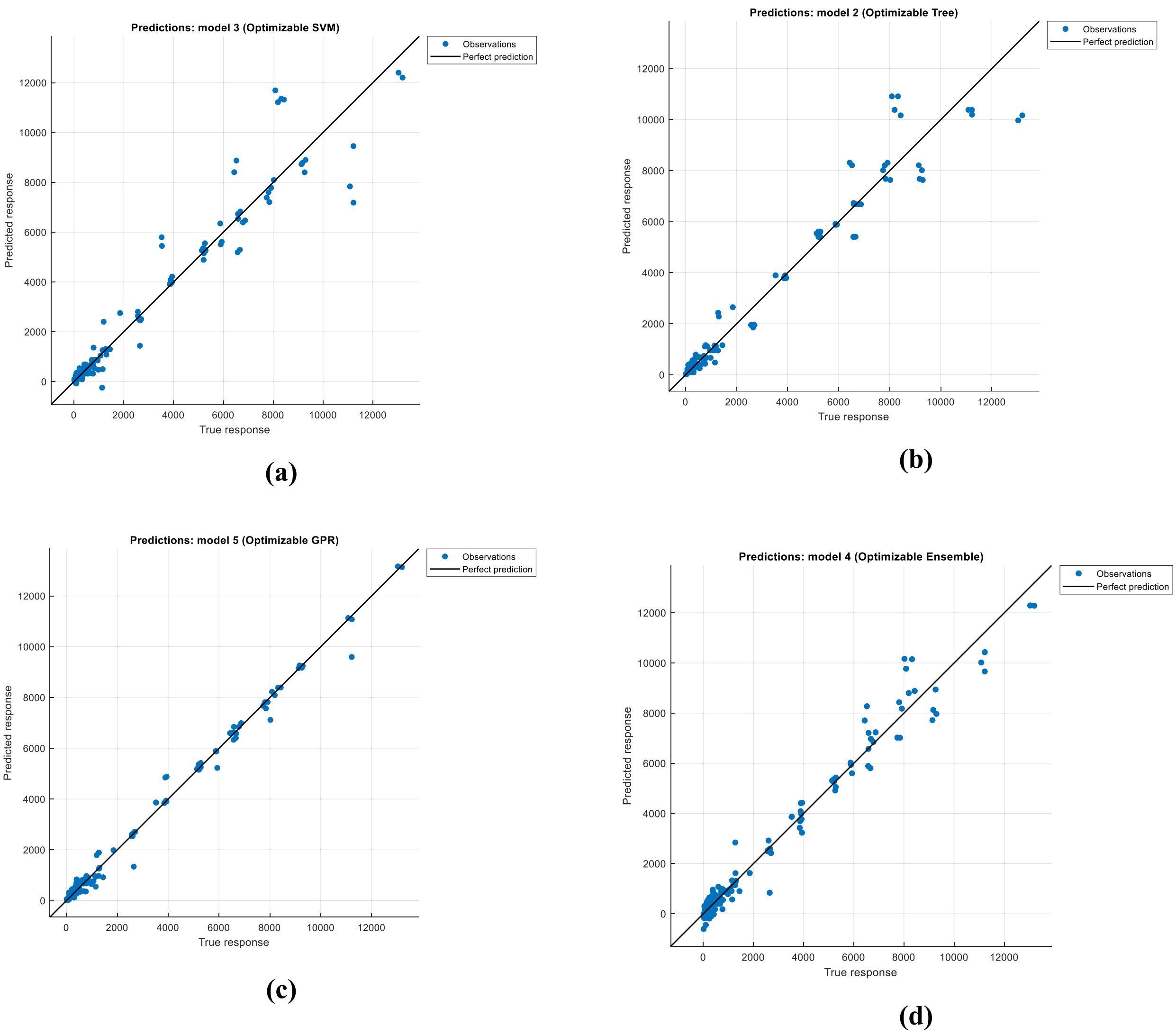


FIGURE 9. Predicted response Vs true response for a) Optimizable SVM b) Optimizable Tree c) Optimizable GPR d) Optimizable Ensemble.

TABLE 6. Dependency of various predictors on current consumption.

Predictors	Hop Depth	No of Motes	Advertising	Backbone	Routing	Reporting interval (s)	Payload size (Bytes)	Downstream frame size	Supply voltage	Path stability
Importance (w.r.t current consumption)	2148.7	101.7	4.6	6907.1	1.2	0.2	1	7.3	9.1	0

The actual measurement of current consumption is obtained from the smart mesh IP power and performance calculator, and the lifetime prediction model is validated.

Table 6 shows the interaction between the features to the response variable, the dependency of various parameters on current consumption, which helps reduce the dimensionality of data and thereby reduce the complexity of the model. It is seen that no of motes, hop depth and backbone most affect the current consumption of the wireless sensor network.

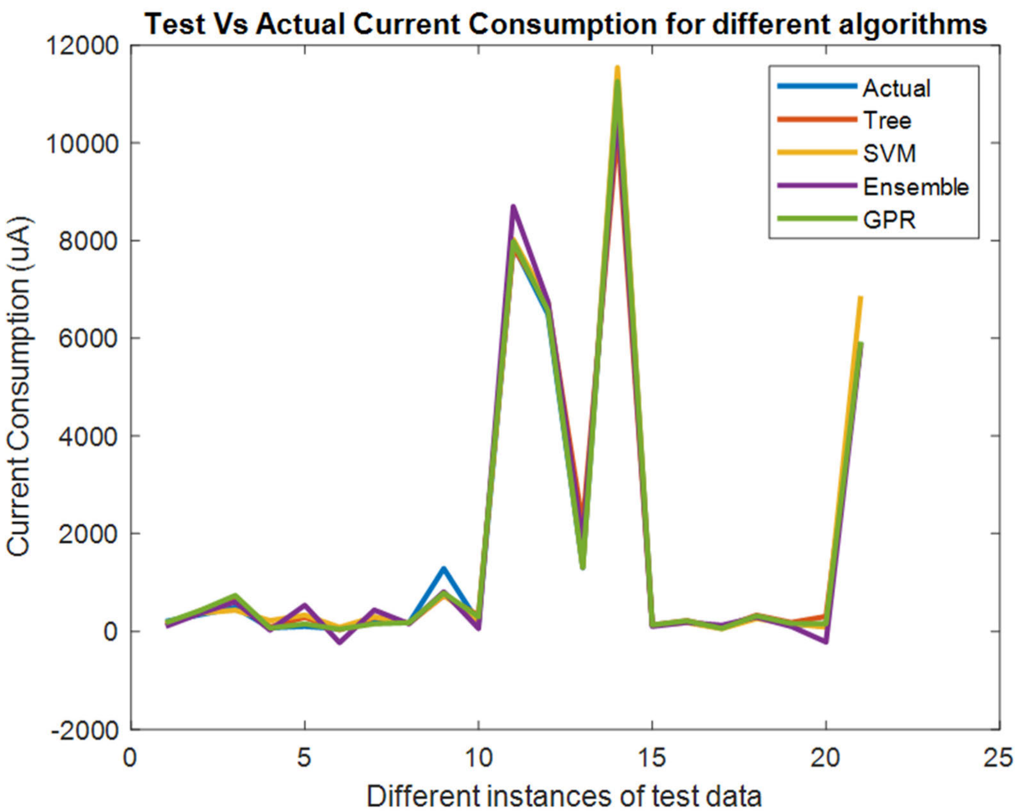
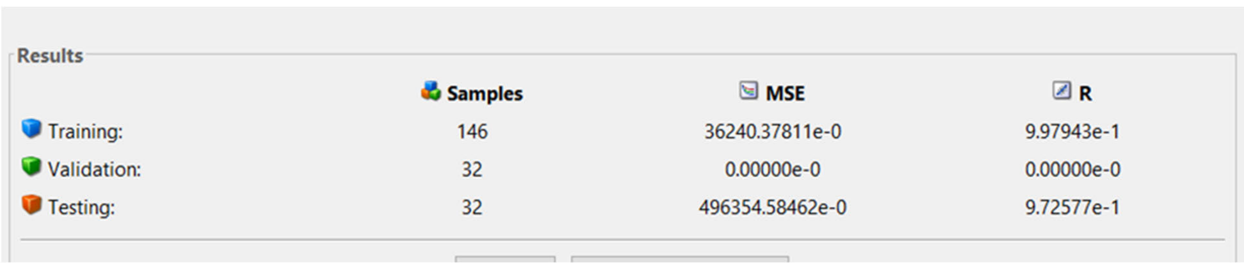


FIGURE 10. Validation of results for different algorithms.



Results

	Samples	MSE	R
Training:	146	36240.37811e-0	9.97943e-1
Validation:	32	0.00000e-0	0.00000e-0
Testing:	32	496354.58462e-0	9.72577e-1

FIGURE 11. Training testing and validation along with their MSE and R-Squared values.

TABLE 7. RMSE of different models.

Algorithm	RMSE
ANFIS hybrid optimization technique	0.01
Back propagation optimization	0.2535
Linear regression	0.092
Optimizable tree	0.02
Optimizable SVM	0.0081
Optimizable ensemble	0.0116
Optimizable Gaussian process regression	0.00408

Again, using 70% of data for training, 15% for validation, and 15% for testing using neural network training tool of MATLAB with Bayesian regularization following mean square error and R-squared values are obtained as shown in Fig. 11. The best training performance is observed at the 102nd epoch, as shown in Fig. 7. Fig. 8 shows the predicted and actual response at different iteration when trained using neural network training. The Bayesian regularization technique minimizes squared errors and weights and optimized learning parameters, as shown in Fig. 9.

B. RESULTS: CH SELECTION USING ML

The RMSE values obtained from the ANFIS model and various ML regression models are shown in Table 7. Fig. 15 shows the predicted Vs. True response of the clustering model obtained using optimizable GPR. The results

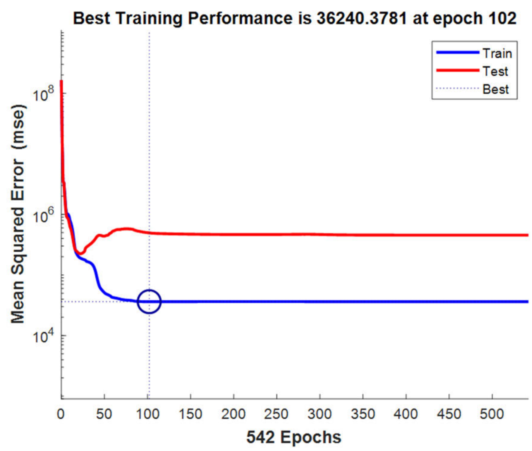


FIGURE 12. Mean squared error for training and testing datasets.

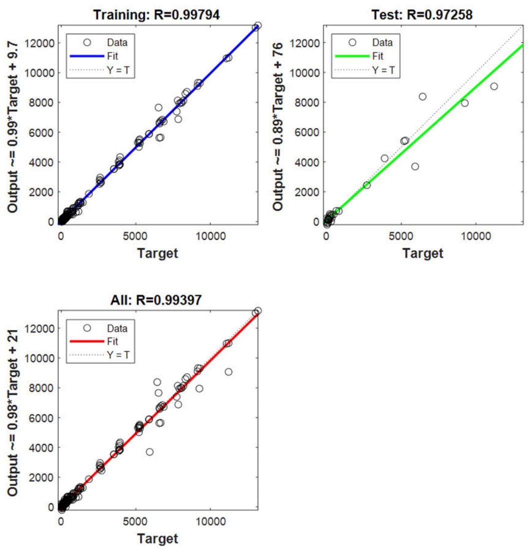


FIGURE 13. Predicted response Vs true response at different iteration.

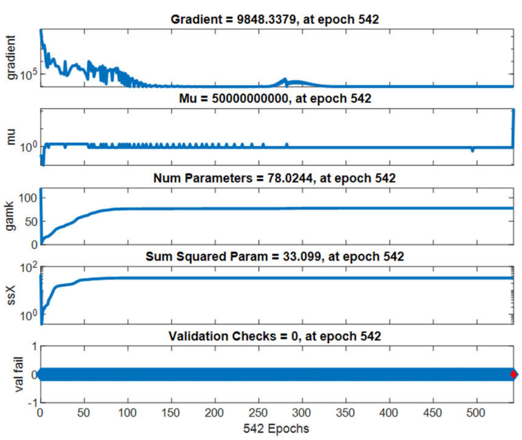


FIGURE 14. Optimized values of different hyperparameters.

indicate that the R-squared value for this algorithm is close to one. Fig. 16 shows the Minimum Mean Squared (MSE) error using the GPR algorithm with Bayesian optimization.

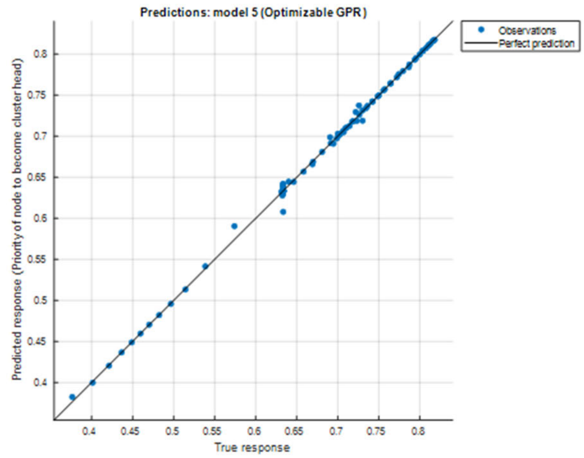


FIGURE 15. Predicted Vs true response for CH selection.

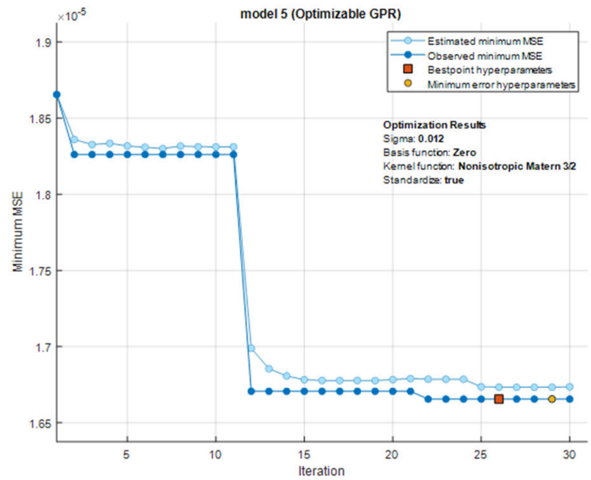


FIGURE 16. Minimum MSE plot for optimizable GPR.

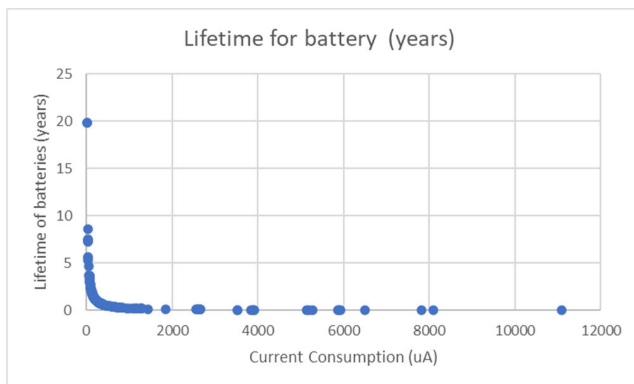


FIGURE 17. Battery lifetime Vs. current consumption.

Battery life is calculated as

$$\text{Battery life (hours)} = \frac{\text{Battery capacity (mAh)}}{\text{Average Current (mA)}} \tag{26}$$

For a Tadiran TL4903AA with a capacity of 2160 mAh, the variation in battery life with current consumption is shown in Fig. 17.

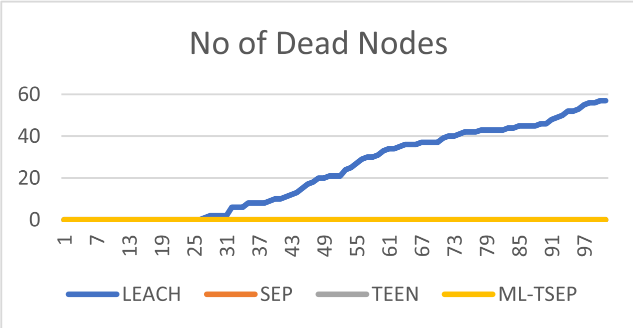


FIGURE 18. Number of dead nodes in clustering protocols after 100 iterations.

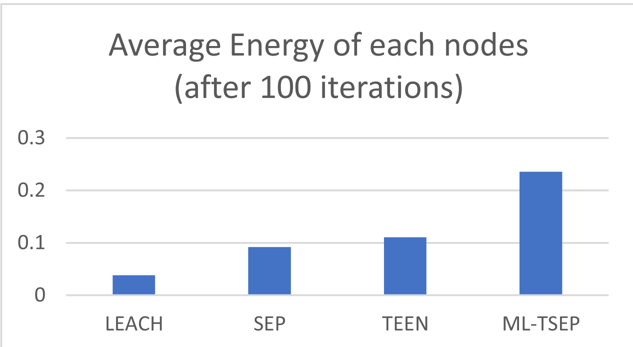


FIGURE 19. Average energy of different clustering protocols after 100 iterations.

A comparison of various protocols like TEEN, SEP, LEACH, and Machine Learning based Threshold Sensitive Stable Election Protocol (ML-TSEP) protocol is carried out in terms of the average energy of each node and number of dead nodes as shown in Fig. 18 and Fig. 19.

V. CONCLUSION

This research work combines intelligent clustering and routing protocols to improve energy consumption and the lifetime of wireless sensor nodes. In this work, the energy consumption, data latency, and build time of sensor nodes are predicted based on various parameters that affect the dynamic behaviour of WSNs, and the factors that most affect the response of the predictive model are identified. Predicting the lifetime of sensor nodes avoids the problems of the constant replacement of batteries, particularly for sensor nodes deployed in remote areas. The most affected network current consumption factors are hop depth, number of motes, and backbone. The results for lifetime prediction are validated with the results obtained from the SmartMesh IP tool. The GPR model for current consumption prediction shows significant improvement in RMSE, R-squared value, and MAE. Apart from this, the priority of CHs is predicted using ML techniques. The priority of a node to become cluster head acts as an input to the modified Threshold Sensitive Stable Election Protocol (ML-TSEP), which selects the cluster head and transmits the data from the sensor nodes to the CHs. The cluster head prediction based on GPR shows significant improvement in RMSE compared to the ANFIS model.

REFERENCES

[1] A. M. George and S. Y Kulkarni, "Performance of power converters for ultra low power systems: A review," in *Proc. 2nd Int. Conf. Adv. Electron., Comput. Commun. (ICAECC)*, Feb. 2018, pp. 1–5, doi: 10.1109/ICAECC.2018.8479512.

[2] A. M. George and S. Y. Kulkarni, "Characterization of battery life of an IoT based wireless networked office lighting system," in *Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT)*, Jul. 2020, pp. 1–6, doi: 10.1109/CONECCT50063.2020.9198419.

[3] N. Srilakshmi and A. K. Sangaiah, "Selection of machine learning techniques for network lifetime parameters and synchronization issues in wireless networks," *J. Inf. Process. Syst.*, vol. 15, no. 4, pp. 833–852, Aug. 2019.

[4] L. Rodrigues, C. Montez, G. Budke, F. Vasques, and P. Portugal, "Estimating the lifetime of wireless sensor network nodes through the use of embedded analytical battery models," *J. Sensor Actuator Netw.*, vol. 6, no. 2, p. 8, Jun. 2017, doi: 10.3390/jsan6020008.

[5] S. Radhika and P. Rangarajan, "On improving the lifespan of wireless sensor networks with fuzzy based clustering and machine learning based data reduction," *Appl. Soft Comput.*, vol. 83, Oct. 2019, Art. no. 105610, doi: 10.1016/j.asoc.2019.105610.

[6] V. K. Arora, V. Sharma, and M. Sachdeva, "A survey on leach and other's routing protocols in wireless sensor network," *Optik*, vol. 127, no. 16, pp. 6590–6600, 2016, doi: 10.1016/j.ijleo.2016.04.041.

[7] I. Daanoune, B. Abdennaceur, and A. Ballouk, "A comprehensive survey on LEACH-based clustering routing protocols in wireless sensor networks," *Ad Hoc Netw.*, vol. 114, Apr. 2021, Art. no. 102409, doi: 10.1016/j.adhoc.2020.102409.

[8] S. Bharany, S. Sharma, S. Badotra, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Energy-efficient clustering scheme for flying ad-hoc networks using an optimized LEACH protocol," *Energies*, vol. 14, no. 19, p. 6016, Sep. 2021.

[9] A. Al-Shaikh, H. Khattab, and S. Al-Sharaeh, "Performance comparison of LEACH and LEACH-C protocols in wireless sensor networks," *J. ICT Res. Appl.*, vol. 12, no. 3, pp. 219–236, 2018.

[10] A. Yadav, S. Kumar, and S. Vijendra, "Network life time analysis of WSNs using particle swarm optimization," *Proc. Comput. Sci.*, vol. 132, pp. 805–815, Jan. 2018.

[11] G. R. Asha, "Energy efficient clustering and routing in a wireless sensor networks," *Proc. Comput. Sci.*, vol. 134, pp. 178–185, Jan. 2018.

[12] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proc. 33rd Annu. Hawaii Int. Conf. Syst. Sci.*, 2000, p. 10.

[13] M. Elshrkawey, S. M. Elsherif, and M. E. Wahed, "An enhancement approach for reducing the energy consumption in wireless sensor networks," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 30, no. 2, pp. 259–267, Apr. 2018, doi: 10.1016/j.jksuci.2017.04.002.

[14] G. Smaragdakis, I. Matta, and A. Bestavros, "SEP: A stable election protocol for clustered heterogeneous wireless sensor networks," in *Proc. 2nd Int. Workshop Sensor Actor Netw. Protocols Appl. (SANPA)*, vol. 3, 2004, pp. 1–11.

[15] A. Kashaf, N. Javaid, Z. A. Khan, and I. A. Khan, "TSEP: Threshold-sensitive stable election protocol for WSNs," in *Proc. 10th Int. Conf. Frontiers Inf. Technol.*, Dec. 2012, pp. 164–168.

[16] S. Sharma, D. Sethi, and P. Bhattacharya, "Artificial neural network based cluster head selection in wireless sensor network," *Int. J. Comput. Appl.*, vol. 119, no. 4, pp. 34–41, Jun. 2015.

[17] Y. Han, G. Li, R. Xu, J. Su, J. Li, and G. Wen, "Clustering the wireless sensor networks: A meta-heuristic approach," *IEEE Access*, vol. 8, pp. 214551–214564, 2020.

[18] A. Seyyedabbasi, G. Dogan, and F. Kiani, "HEEL: A new clustering method to improve wireless sensor network lifetime," *IET Wireless Sensor Syst.*, vol. 10, no. 3, pp. 130–136, Jun. 2020.

[19] N. Aslam, K. Xia, and M. U. Hadi, "Optimal wireless charging inclusive of intellectual routing based on SARSA learning in renewable wireless sensor networks," *IEEE Sensors J.*, vol. 19, no. 18, pp. 8340–8351, Sep. 2019.

[20] É. Morin, M. Maman, R. Guizzetti, and A. Duda, "Comparison of the device lifetime in wireless networks for the Internet of Things," *IEEE Access*, vol. 5, pp. 7097–7114, 2017.

[21] X. Vilajosana, Q. Wang, F. Chraim, T. Watteyne, T. Chang, and K. S. J. Pister, "A realistic energy consumption model for TSCH networks," *IEEE Sensors J.*, vol. 14, no. 2, pp. 482–489, Feb. 2014, doi: 10.1109/JSEN.2013.2285411.
[22] B. Martinez, M. Montón, I. Vilajosana, and J. D. Prades, "The power of models: Modeling power consumption for IoT devices," *IEEE Sensors J.*, vol. 15, no. 10, pp. 5777–5789, Oct. 2015, doi: 10.1109/JSEN.2015.2445094.
[23] L.-O. Varga, G. Romaniello, M. Vučinić, M. Favre, A. Banciu, R. Guizzetti, C. Planat, P. Urard, M. Heusse, F. Rousseau, and O. Alphand, "GreenNet: An energy-harvesting ip-enabled wireless sensor network," *IEEE Internet Things J.*, vol. 2, no. 5, pp. 412–426, Oct. 2015, doi: 10.1109/JIOT.2015.2425431.
[24] Q. Wang, M. Hempstead, and W. Yang, "A realistic power consumption model for wireless sensor network devices," in *Proc. 3rd Annu. IEEE Commun. Soc. Sensor Ad Hoc Commun. Netw. (SECON)*, vol. 1, Sep. 2006, pp. 286–295, doi: 10.1109/SAHCN.2006.288433.
[25] J. Li and P. Mohapatra, "Analytical modeling and mitigation techniques for the energy hole problem in sensor networks," *Pervasive Mobile Comput. J.*, vol. 3, no. 3, pp. 233–254, Jun. 2007, doi: 10.1016/j.pmcj.2006.11.001.
[26] Q. Wang and W. Yang, "Energy consumption model for power management in wireless sensor networks," in *Proc. 4th Annu. IEEE Commun. Soc. Conf. Sensor, Mesh Ad Hoc Commun. Netw.*, Jun. 2007, pp. 142–151, doi: 10.1109/SAHCN.2007.4292826.
[27] H.-Y. Zhou, D.-Y. Luo, Y. Gao, and D.-C. Zuo, "Modeling of node energy consumption for wireless sensor networks," *Wireless Sensor Netw.*, vol. 3, no. 1, pp. 18–23, 2011, doi: 10.4236/wsn.2011.31003.
[28] B. Kan, L. Cai, L. Zhao, and Y. Xu, "Energy efficient design of WSN based on an accurate power consumption model," in *Proc. Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Sep. 2007, pp. 2751–2754, doi: 10.1109/WICOM.2007.683.
[29] D. P. Kumar, A. Tarachand, and C. S. R. Annavarapu, "Machine learning algorithms for wireless sensor networks: A survey," *Inf. Fusion*, vol. 49, pp. 1–25, Sep. 2019, doi: 10.1016/j.inffus.2018.09.013.
[30] P. K. R. Maddikunta, G. Srivastava, T. R. Gadekallu, N. Deepa, and P. Boopathy, "Predictive model for battery life in IoT networks," *IET Intell. Transp. Syst.*, vol. 14, no. 11, pp. 1388–1395, Nov. 2020.
[31] X.-C. Xi, A.-N. Poo, and S.-K. Chou, "Support vector regression model predictive control on a HVAC plant," *Control Eng. Pract.*, vol. 15, no. 8, pp. 897–908, Aug. 2007, doi: 10.1016/j.conengprac.2006.10.010.
[32] J. Wang and J. Hu, "A robust combination approach for short-term wind speed forecasting and analysis – combination of the ARIMA (autoregressive integrated moving average), ELM (extreme learning machine), SVM (support vector machine) and LSSVM (least square SVM) forecasts using a GPR (Gaussian process regression) model," *Energy*, vol. 93, pp. 41–56, Dec. 2015, doi: 10.1016/j.energy.2015.08.045.
[33] P. Nayak and A. Devulapalli, "A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime," *IEEE Sensors J.*, vol. 16, no. 1, pp. 137–144, Jan. 2015.
[34] J.-M. Kim, S.-H. Park, Y.-J. Han, and T.-M. Chung, "Chef: Cluster head election mechanism using fuzzy logic in wireless sensor networks," in *Proc. 10th Int. Conf. Adv. Commun. Technol.*, vol. 1, Feb. 2008, pp. 654–659, doi: 10.1109/ICACT.2008.4493846.
[35] T. Sharma and B. Kumar, "F-mchel: Fuzzy based master cluster head election leach protocol in wireless sensor network," *Int. J. Comput. Sci. Telecommun.*, vol. 3, no. 10, pp. 8–13, 2012.
[36] M. Mittal and K. Kumar, "Data clustering in wireless sensor network implemented on self organization feature map (SOFM) neural network," in *Proc. Int. Conf. Comput., Commun. Automat. (ICCCA)*, Apr. 2016, pp. 202–207, doi: 10.1109/CCAA.2016.7813718.
[37] Z. Wang, H. Ding, B. Li, L. Bao, and Z. Yang, "An energy efficient routing protocol based on improved artificial bee colony algorithm for wireless sensor networks," *IEEE Access*, vol. 8, pp. 133577–133596, 2020, doi: 10.1109/ICACT.2008.4493846.
[38] Y. Zhou, N. Wang, and W. Xiang, "Clustering hierarchy protocol in wireless sensor networks using an improved PSO algorithm," *IEEE Access*, vol. 5, pp. 2241–2253, 2017, doi: 10.1109/ACCESS.2016.2633826.
[39] C. P. Kurian, V. I. George, R. S. Aithal, and J. Bhat, "Fuzzy Logic based window blind controller maximizing visual comfort, thermal comfort and energy conservation suitable for tropical climate," *J. Inst. Eng. Archit. Eng. Div.*, vol. 89, pp. 14–22, Apr. 2008.
[40] S. Varghese, C. Kurian, V. George, M. Varghese, and T. S. Kumar, "Climate model based test workbench for daylight-artificial light integration," *Lighting Res. Technol.*, vol. 51, no. 5, pp. 774–787, Aug. 2019.
[41] A. M. George and S. Kulkarni, "Cluster based routing protocols for IoT application," *Int. J. Comput. Netw. Inf. Secur.*, vol. 11, no. 5, pp. 43–49, May 2019, doi: 10.5815/ijcnis.2019.05.06.

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