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Energy Map Construction using Adaptive Alpha Grey Prediction Model in WSNs

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***Abstract*—**Wireless Sensor Networks can be used to monitor the physical phenomenon in such areas where human approach is nearly impossible. Hence the limited power supply is the major constraint of the WSNs due to the use of non-rechargeable batteries in sensor nodes. A lot of researches are going on to reduce the energy consumption of sensor nodes. Energy map can be used with clustering, data dissemination and routing techniques to reduce the power consumption of WSNs. Energy map can also be used to know which part of the network is going to fail in near future. In this paper, Energy map is constructed using the prediction based approach. Adaptive alpha GM(1,1) model is used as the prediction model. GM(1,1) is being used worldwide in many applications for predicting future values of time series using some past values due to its high computational efficiency and accuracy.

***Keywords*—**Adaptive Alpha GM(1,1) Model, Energy Map, Prediction Based Data Reduction, Wireless Sensor Networks

I. INTRODUCTION

WIRELESS Sensor Network consists of tiny sensor nodes deployed over a geographical area for monitoring physical phenomena like temperature, humidity, vibrations, seismic events, and so on [8]. WSNs consist of four main subsystems: (1) Sensing subsystem, to sense the physical phenomenon (2) Processing subsystem, consists of microcontroller and memory for local data processing (3) Communication subsystem, for wireless data transmission (4) Power supply, for providing supply to other subsystems to perform their tasks. But the limited power supply due to the non-rechargeable batteries used in sensor nodes is the major constraint in WSNs. Communication subsystem is the major cause of energy consumption because to transmit single bit to 100 meters consumes the same power what a processing system consumes to process 1000 instructions. A lot of researches are going on all over the world to reduce the energy consumption of sensor nodes.

Energy map is the mean to reduce the energy consumption and improve lifetime of the WSNs. Energy map can also be used to know which part of the network is going to fail in near future and we can redeploy new sensor nodes to prevent network failure.

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In this paper, Energy map is constructed using the prediction based approach. Adaptive alpha GM(1,1) model is used as the prediction model which is being used worldwide in many applications for predicting future values in time series using some past values due to its high computational efficiency and accuracy.

The paper is arranged as: Section II gives a brief overview of the Energy map, Section III discusses about prediction based approach, Section IV gives overview of GM(1,1) Model and in Section V, formulation of adaptive alpha GM(1,1) model is presented. In Section VI, Prediction based data reduction approach is given. In Section VII, Simulation and results have been presented and in Section VIII, conclusion has been made.

II. ENERGY MAP

Just like a weather map, a scan of residual energy in the sensor network can be made which will give the information about the available remaining energy at each node deployed in the sensor network. This scan of residual energy information in each part of the network is called the energy map and can aid in prolonging the lifetime of the network [2].

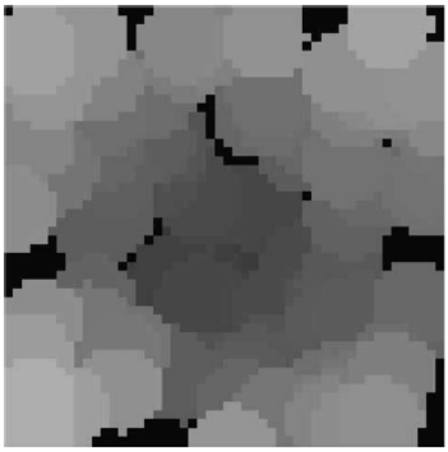

Fig. 1 Residual energy scan (Energy map) in WSNs

An energy map is shown in figure 1 which represents the sensor network as a gray level image, in which light shaded areas are representing regions with more remaining energy, and the dark shaded regions are representing less energy.

By using the energy map, one can determine if any part of the network is about to fail in near future due to depletion of energy [1]. By the knowledge of low energy areas, incremental deployment of sensors can be done. The best location or the choice of monitoring node can also be made using energy map. A monitoring node is a special node responsible for collecting information from sensor nodes.

III. Prediction Based Data Reduction Approach

Energy map is basically a scan of available remaining energy (i.e. residual energy) at each sensor node in deployed in sensor field. A basic way of thinking about energy map construction is one in which periodically each node sends to the monitoring node its available energy which can be called as naïve approach. As the sensor networks may have lots of nodes with limited resources, the amount of energy spent in the naïve approach will be prohibitive [1].

Basically, each node sends the parameters of the model describing its energy drop to the monitoring node and the monitoring node updates locally the information about the available energy at each node using these parameters. According to prediction based approach if a node is able to predict the amount of energy it will spend, it can send this information to the monitoring node and avoids sending energy information during the period that the model can describe satisfactorily the energy dissipation. Then, if a node can efficiently predict the amount of energy it will dissipate in near future, a significant energy can be saved in the process of constructing the energy map of a sensor network [3].

In this paper, the prediction based approach is used to construct the energy map, according to which sensor nodes need not to send its residual energy information to monitoring node for every round. Sensor node will send its energy information if there will be significant drop in its residual energy. In this approach, number of transmissions of energy information will be reduced between sensor node and monitoring node which saves a significant amount of energy for constructing energy map. Reduction of number of transmissions will depend on the accuracy of the prediction model used to predict the future values of residual energy of sensor nodes. On the basis of residual energies of sensor nodes deployed over the sensor field, monitoring node construct an energy map and can know which part of the network is going to fail in near future so that new sensor nodes can be deployed to prevent the network failure.

IV. GM(1,1) Model

Grey models are most widely used predictive models for predicting the future values of a time series using some recent previous values. GM(n,m) denotes a grey model, where n is the order of the differential equation and m is the number of variables. GM (1,1) is most widely used Grey Model because of its computational efficiency. GM(1,1) is pronounces as "Grey model first order one variable". GM(1,1) model is being used worldwide in economic, social, financial, scientific and technological, agricultural, industrial, transportation, mechanical, meteorological, geological, medical, military etc. applications [4,5].

V. Formulation of Adaptive Alpha GM(1,1) Model

Let $X_{(0)}$ is the primitive data used for predictions and can be expressed as

$$X_{(0)} = [x_{(0)}(1)\ x_{(0)}(2)\ x_{(0)}(3) \ldots\ldots x_{(0)}(t)] \qquad t < n \tag{1}$$

Where n is the length of the data to be predicted. To remove the randomness of the primitive data, it is subjected to the Accumulation Generating Operator (AGO) and the accumulated data can be expressed as

$$X_{(1)} = [x_{(1)}(1)\ x_{(1)}(2)\ x_{(1)}(3) \ldots\ldots\ldots\ldots\ldots\ldots x_{(1)}(t)] \tag{2}$$

Where, $$x_{(1)}(t) = \sum_{i=1}^{t} x_{(1)}(i) \tag{3}$$

Then, $x_{(0)}(t) + a\ x_{(1)}(t) = b$ is referred to as basic form of GM(1,1) model. Let $Z_{(1)}$ is the sequence generated from $X_{(1)}$ by adjacent neighbor mean and can be expressed as a sequence $Z_{(1)}=[z_{(1)}(1)\ z_{(1)}(2)\ z_{(1)}(3) \ldots\ldots z_{(1)}(t)]$ where $z_{(1)}(t) = \text{alpha}\times x_{(1)}(t)+(1-\text{alpha})\times x_{(1)}(t-1)$ and for traditional GM(1,1) model, alpha (weighing factor) is taken as 0.5.

a (developing coefficient) and b (driving coefficient) are the grey model parameters and can be calculated by Least square method using the equation given as

$$[a,b]^T = [(BB^T)^{-1}B^TA] \tag{4}$$

Where, $$B=\begin{bmatrix} -z_{(1)}(2) & 1 \\ -z_{(1)}(3) & 1 \\ \vdots & \vdots \\ -z_{(1)}(t) & 1 \end{bmatrix} \quad \text{and} \quad A=\begin{bmatrix} x_{(0)}(2) \\ x_{(0)}(3) \\ \vdots \\ x_{(0)}(t) \end{bmatrix}$$

Now, Whitenization (or image) equation of GM(1,1) can be expressed as

$$\frac{dx_{(1)}}{dt} + a x_{(1)} = b \tag{5}$$

According to the Whitenization equation, the solution of the $x_{(1)}(t)$ at time (t+1) can be expressed as

$$x_{P(1)}(t+1) = [x_{(0)}(1)-b/a]e^{-at} + b/a \tag{6}$$

To obtain the predicted value of the primitive data at time (t+1), the IAGO is used to establish the following grey model.

$$x_{P(0)}(t+1) = [x_{(0)}(1)-b/a]e^{-at}(1-e^{a}) \tag{7}$$

The prediction error can be computed as

$$e(t+1) = \left|x_{P(0)}(t+1)-x_{(0)}(t+1)\right| \tag{8}$$

The percentage error can be computed as

$$e\,(t+1)(\%) = \frac{\left|x_{P(0)}(t+1)-x_{(0)}(t+1)\right|}{x_{(0)}(t+1)}\times 100 \tag{9}$$

A. Calculation of alpha (Weighing factor)

For adaptive alpha GM(1,1) model, value of z(t) is given as

$$z_{(1)}(t) = alpha(t)\times x_{(1)}(t)+\{1-alpha(t)\}\times x_{(1)}(t-1) \quad (10)$$

Here, alpha(t) is taken as variable ranging between 0 and 1, which is determined by Average slope technique [7] given as follows

1) Calculate average slope coefficient $alpha_{avg}$ as

$$alpha_{avg} = \sqrt[t-1]{\frac{x_{(0)}(t)}{x_{(0)}(1)}} \quad (11)$$

2) Calculate the relative position $alpha_{(i-1)}$ values for the data points (excluding the first and the last points that are forced to match the data values of the real system end points) to force the data of the system model to equate the data of the practical system model.

$$alpha_{(i-1)} = \frac{\log(x_{(0)}(i-1)/x_{(0)}(1))}{\log(alpha_{avg})} \qquad i = 3,4,.....t \quad (12)$$

$alpha_{(1)} = 0$ and $alpha_{(t)} = 1$

VI. Algorithm for Energy Map Construction

In this approach, sensors and monitoring node will use same length prediction queues to store the predicted information data and implement same prediction model. Information data values to be used for predicting future values must be same for sensors and monitoring node. Monitoring node will have 'n' numbers of prediction queues for 'n' sensors. In each round, sensors will sense the actual information data and will calculate the prediction value for corresponding round. Then sensor will calculate the prediction error between actual sensed value and the predicted value. If this error comes less than the predefined prediction error threshold denoted by '$e_{threshold}$', sensor will not send this value to the monitoring node. But if the prediction error exceeds the predefined prediction error threshold ($e_{threshold}$), sensor will update this value in its queue and will use it for further predictions and simultaneously send this value to the monitoring node. Monitoring node will update this value in its prediction queue of corresponding sensor and will also use this value for further predictions. This approach reduces a number of data transmissions between sensors and monitoring node. The reduction in such transmissions will result in reducing the energy consumption of sensors' battery. In this way, we can enhance the lifetime of the batteries so that it can work for a long time.

VII. Simulation and Results

In this paper, simulations have been carried out using MATLAB taking 100 randomly deployed sensor nodes over the square field of 100×100 and the BS location is taken at (50,120). In every round each sensor node is transmitting the data packets and energy information packets to the BS. But if the prediction of the energy information is accurate then nodes need not to transmit the energy information packets to the BS.

TABLE I
PARAMETERS USED FOR SIMULATION

Parameter	Value	Units
Number of sensor nodes	100	
Node distribution	(0,0) to (100,100)	meter
BS location	(50,120)	meter
Initial energy of nodes	0.1	Joules
Data packet length	4000	bits
Information bits	500	bits
E_{elec}	50	nJ/bit
ϵ_{mp}	0.0013	nJ/bit/m^4
ϵ_{fs}	10	nJ/bit/m^2
E_{grey}	5	nJ/bit
Window size	3	
Maximum acceptable prediction error	3	%

A. Energy Consumption Model

The depleted energy of the sensor nodes to transmit l bits over a distance between sensor nodes to BS for each round is given by the expression.

$$E_{Tx}(l,d) = E_{Tx\text{-}elec}(l) + E_{Tx\text{-}amp}(l,d) \quad (13)$$

$$E_{Tx}(l,d) = l\,E_{elec} + l\,\epsilon_{fs}d^2 \qquad \text{if } d \le d_o \quad (14)$$

$$E_{Tx}(l,d) = l\,E_{elec} + l\,\epsilon_{mp}d^4 \qquad \text{if } d > d_o \quad (15)$$

$$\text{Where } d_o = (\epsilon_{fs} / \epsilon_{mp})^{1/2}$$

Where, E_{elec} represents power consumption for transmitter and receiver processing 1 bit data, ϵ_{mp} represents power consumption for emission amplifier transmitting 1 bit to an area of one square meter in multipath channel, ϵ_{fs} represents power consumption for emission amplifier transmitting 1 bit to an area of one square meter in free space, d is the range of signal transmission.

The simulation has been for 100 rounds taking window size as 3 and $e_{threshold}$ as 3%.

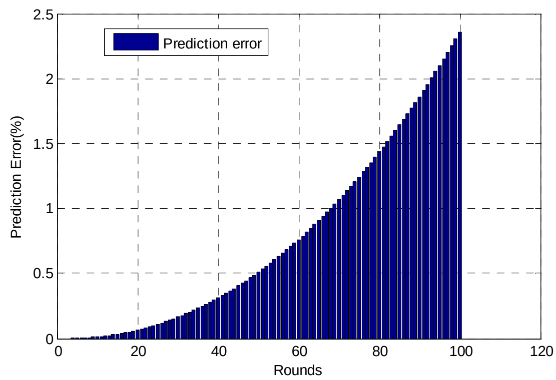

Fig. 2 Percentage prediction error plot for 100 rounds

Figure 2 is showing the Percentage prediction error (e %) Vs number of rounds plot. The Mean absolute percentage error (MAPE) is calculated as 0.7681%.

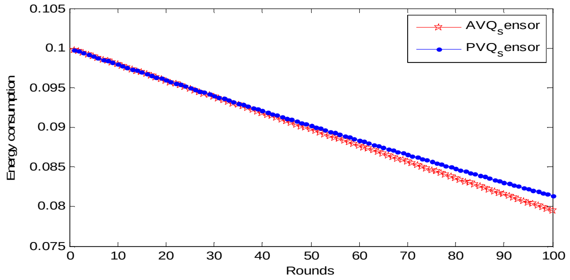

Fig. 3 Energy Depletion plot

Figure 3 shows the comparison between actual values and predicted values of energy consumption for 100 rounds. AVQ_{sensor} is showing actual values and PVQ_{sensor} is showing predicted values of energy consumption. At the place where prediction error exceeds prediction error threshold, actual value replaces predicted value.

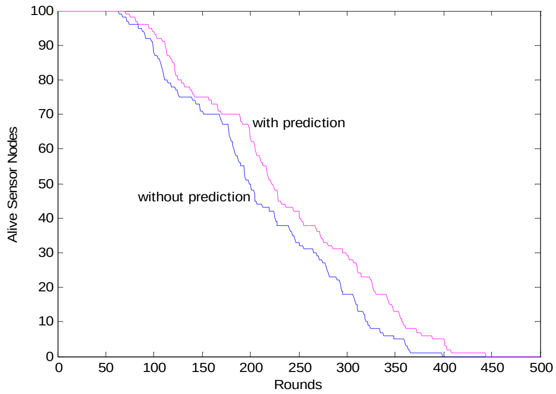

Fig. 4 Lifetime analysis plot

Figure 4 is showing the lifetime analysis of sensor network according to which lifetime of network in direct approach with prediction is more than direct approach without prediction approach. Results are shown in table which is showing that nodes in direct approach without prediction started to die before as in direct approach with prediction.

VIII. Conclusion

From the above discussion, it is clear that if Adaptive alpha GM(1,1) prediction model based approach is implemented to construct the energy map, a significant number of transmissions of information message can be reduced which will result in reduction of energy consumption in sensor node. Result is showing that out of 100 rounds, there is no need to transmit energy information to the BS.

TABLE II
Lifetime Analysis of Sensor Network

Dead nodes (%)	Without Prediction Approach	With Prediction Approach
1	64	71
10	100	112
25	126	142
50	199	222
75	279	311
100	399	450

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