Development of Energy Harvesting Wireless Sensor Networks using An Energy Aware Distributed Clustered Routing Protocol Mechanism based on Neural network-solar energy prediction model.

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Abstract- Energy harvesting wireless sensor networks (EH-WSNs) have been widely used in various areas in recent years. Unlike battery-powered wireless sensor networks, EH-WSNs are powered by energy harvested from ambience. This change calls for new designs on routing protocols in EH-WSNs. This paper proposes a novel energy-aware distributed clustering routing protocol for EH-WSNs, it takes the node current residual energy and the harvested energy in a short term prediction horizon into cluster heads election process of the distributed clustering routing. A neural network based solar energy prediction model is exploited to make the protocol energy-aware. Nodes with higher residual energy and stronger energy harvesting capabilities thus have higher probability of being cluster heads. The proposed routing algorithm is compared with LEACH (low-energy adaptive clustering hierarchy) in terms of the number of awake nodes and network throughput. Simulation results show that the proposed clustering routing has stronger ability to balance energy consumption among sensor nodes and increases the network throughput by about 30% over LEACH.

I. Introduction

Wireless sensor networks (WSNs) have been widely applied in various areas such as environmental monitoring, industrial control and tracking [1]. For battery-powered WSNs, the biggest challenge is how to extend the lifetime of the network in condition of the limited battery capacity. In recent years, energy harvesting technologies have gained increasingly high attention as it enables WSNs to break through the bottle neck of battery capacity [2] [3]. Instead of batteries, EH-WSNs work on the power harvested from ambience. They have the potential to work permanently unless hardware breaks down. However, the energy distribution of nodes is not even due to some uncontrollable factors (solar panel angles, shadows, etc.). So the aim of routing design for EH-WSNs is changed from extending the lifetime of a sensor network to maximizing the network throughput under given environment power constraints.

This change calls for new designs on routing protocols in EH-WSNs. Many research activities have been carried out in recent years to develop routing protocols for EH-WSNs. In [4], an opportunistic routing protocol (EHOR) for multi-hop EH-WSNs has been proposed. It takes energy constraints into account and utilizes a regioning approach to choose an optimal forwarder. Voigt *et al.* proposed the solar-aware directed diffusion [5], which extends the standard directed diffusion protocol by adding solar fields to its headers. In [6], an energy-aware routing mechanism based on geographic routing was proposed, which modifies the Ad-hoc On-demand Distance Vector (AODV) routing mechanism to realize the energy perception routing. Among all the routing protocols for WSNs, LEACH is the most well-known cluster-based protocol. It is designed to minimize energy dissipation in WSNs [7]. Based on it, several protocols have been developed and adapted for EH-WSNs [8]-[10]. However, LEACH is designed under the assumption that the energy consumption of being a cluster head is equal for all sensor nodes, but in reality it varies significantly. In addition, the original LEACH and most of its variations fail to consider each node's energy harvesting capability in the near future in the cluster heads selection process. Some of them take nodes' residual energy into consideration, but little effort has been devoted to introduce energy prediction to the routing design.

Since accurate predictions enable efficient power management and improved performance of EH-WSNs, many research studies have been performed to forecast the solar radiation using artificial neural networks in recent years [11-13]. In [11], a recurrent back-propagation network was established to forecast the daily total solar irradiance with the inputs of the major factors (e.g. solar elevation angle, geographic location, sunshine durations, the day number of a year, the forecast time, etc.). An Elman style based recurrent neural network was proposed to predict solar radiation from the past solar radiation and solar energy in [12]. However, most of the existing solar energy prediction techniques focus solely on improving the energy prediction accuracy. Very few of them apply solar prediction models in the routing design for EH-WSNs, and this is also the case for existing cluster-based routing protocols.

This paper proposes an energy-aware distributed clustering routing protocol for energy harvesting wireless sensor networks. A neural network based solar energy prediction model is exploited to make each sensor node be able to predict its harvested energy in a short term prediction horizon. The predicted energy is used in the cluster heads election process in the proposed clustering routing protocol. Nodes with higher residual energy and predicted energy have higher probability of being cluster heads. The proposed algorithm has stronger ability in balancing energy consumption among sensor nodes by increasing the probability of nodes with higher energy sustainability to be cluster heads and thus increases the network throughput.

The paper is organized as follows. Section II introduces system models used in this paper. In Section III, the proposed energy-aware clustering routing protocol is presented in details. Section IV provides the simulation results and comparisons. Section V concludes the paper.

II. System Models

Cluster-based routing algorithms can be classified into two main categories, namely, the distributed and the centralized. For the distributed ones, all nodes choose themselves to be cluster heads by a predefined probability and then announce its cluster-head status to other nodes. The nodes which are not cluster heads choose the nearest cluster head to join in when they receive the status message. The distributed version of LEACH has advantages over the centralized ones in terms of the response time. In this paper, we choose to design the proposed protocol based on distributed clustering.

A. Network Model

We consider a multihop EH-WSN composed of a number of sensor nodes with energy harvesting capability and a base station (BS) which is fixed and with unlimited power supply. It is assumed that all sensor nodes have the ability to use power control to vary the amount of transmit power to reach the BS. Furthermore, every node has the computation power to support different MAC protocols and to perform signal processing functions. We also assume that all sensors are sensing the environment at a fixed rate and always have data to send to the base station. Data aggregation is used here to reduce the total data message sent. Each node goes to sleeping mode when its energy falls below $E_{cap}/10$ and wakes up when its energy is above $3E_{cap}/10$ (E_{cap} is the node energy capacity).

In the clustering routing, N sensor nodes form clusters with h nodes of them being selected as cluster heads. The operation of clustering routing is divided into rounds with each round containing two phases, i.e., set-up phase and steady-state phase. Clusters are organized in the set-up phase, followed by a steady-state phase when data are transferred from the nodes to the cluster head and on to the BS in frames. Fig. 1 shows an example of cluster formation during a round. Fig. 2 illustrates the operation of clustering routing.

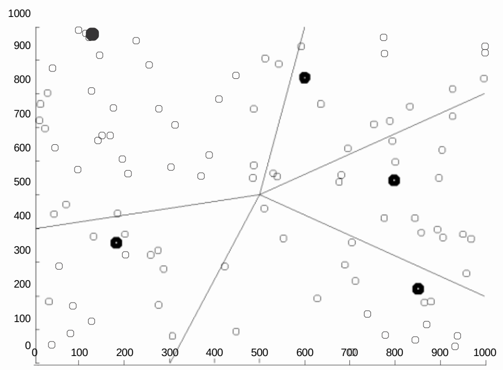

Fig. 1. Cluster formation in a round. Hollow circles represent non-cluster head nodes and solid circles denote cluster heads.

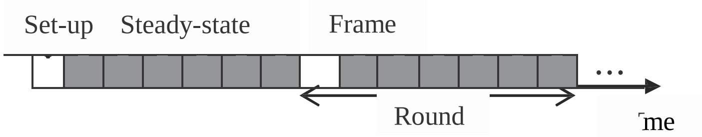

Fig. 2. The operation of clustering routing

B. Radio Model

The same radio energy dissipate model as that in LEACH is used in this paper. The energy consumption of the transmitter is described as

$$E_{TX}(k,d) = E_{elec}k + E_{fs}kd^2, \quad (1)$$

$$E_{TX}(k,d) = E_{elec}k + E_{mp}kd^4, \quad (2)$$

where k is the number of bits of the transmission data and d is the distance. The electronics energy, E_{elec}, depends on factors such as digital coding , modulation, filtering, and spreading of the signal, whereas the amplifier energy $E_{fs}d^2$ or $E_{mp}d^4$, depends on the distance to the receiver and the acceptable bit-error rate. (1) is used to calculate the transmission energy consumed within a cluster, while (2) is used to calculate such energy from a cluster head to the BS. The energy consumption of the receiver is given by

$$E_{RX} = E_{elec}k, \quad (3)$$

The energy for data aggregation is set as E_{DA}=5 nJ/bit/signal.

III. Energy-Aware Clustering Routing Algorithm

In this section, we describe the proposed energy-aware clustering routing algorithm in details. We will first illustrate the neural network-based solar model and then introduce it to the cluster heads election phase of LEACH.

A. Neural Network Based Solar Energy Prediction

Due to the increasing use of solar power in energy harvesting wireless sensor networks, the prediction of solar energy has become critical. Accurate predictions enable efficient power management and improved performance of EH-WSNs. Many research studies have been carried out to forecast the solar radiation in recent years, such as Exponentially Weighted Moving Average (EWMA) [14], Weather Conditioned Moving Average (WCMA) [15], and neural network based forecast models [11]-[13]. Each of them has its own advantages and weaknesses, the discussion of that is beyond the scope of this paper.

All sensor nodes in this study have the ability to harvest solar energy from ambience. Here we use real data about solar energy. The solar data was measured over a 90-day period (a season) for all sensor nodes. Fig. 3 shows the energy availability profile of a sensor node used in this paper on a diurnal scale, with the data from 90 days overlapped.

The energy of the i-th node at the beginning of the r-th round in the d-th day $E(i,d,r)$ can be described as

$$E(i,d,r) = E_{res}(i,d,r) + E_{harv}(i,d,r-1), \quad (4)$$

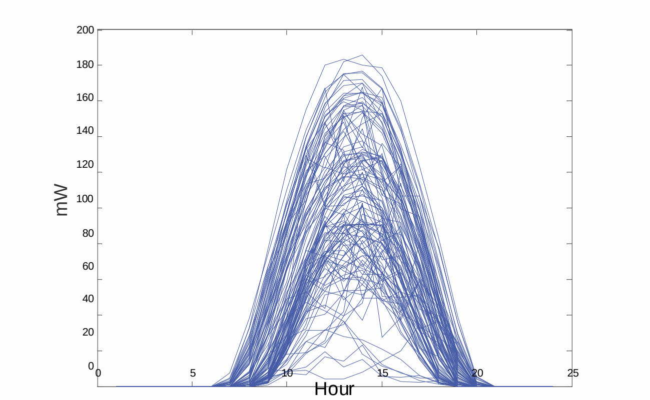

Fig. 3. Solar energy profile (Diurnal).

where $E_{res}(i,d,r)$ and $E_{harv}(i,d,r-1)$ are the residual energy (without taking energy harvesting into consideration) at the beginning of the r-th round and the harvested energy during the (r-1)-th round of the i-th node, respectively.

In this paper, we choose a neural network based solar energy prediction model as the way to estimate the energy that is to be harvested by a node in a short term prediction horizon. The values of harvested energy for all nodes are collected in matrices where each column represents a different hour in a day and each raw represents a different day (Fig. 4). For a given round and a given day, we consider the average energy that can be harvested in that round as a function of the harvested energy in that round in the previous n days and the harvested energy in the previous k rounds in that day, i.e.,

$$E_{pre}(i,d,r) = f_{ANN}(E_{harv}(i,d-1,r),\dots,E_{harv}(i,d-n,r), \\ E_{harv}(i,d,r-1),\dots,E_{harv}(i,d,r-k)) \,. \qquad (5)$$

The neural network is composed of three layers, i.e., input layer, hidden layer, and output layer. Neurons between adjacent layers are fully connected and the connections are opportunely weighted by coefficients. The input layer has n+k neurons and the output layer has 1 neuron, the number of hidden neurons is to be adjusted depending on different desired accuracies, as indicated in Fig. 5.The inputs of the neural network model correspond to the n+k inputs of the function defined above and the output corresponds to $E_{harv}(i,d,r)$. The activation function in the hidden neurons is sigmoid function defined as

$$\sigma(X) = \frac{1}{1+e^{-X}} \,, \qquad (6)$$

We use a supervised learning with error back propagation

day \ hour	··· 8	9	10	11	12 ···
1	3.47	21.53	36.11	87.5	118.75
2	0.69	17.36	48.61	85.42	114.58
3	0.69	25	68.75	111.11	138.19
4	0	9.72	33.33	?	72.22
5	4.86	36.81	80.56	92.88	150.69
6	0.71	16.67	20.14	72.92	125

Fig. 4. Matrix for solar energy prediction (n=3, k=3).

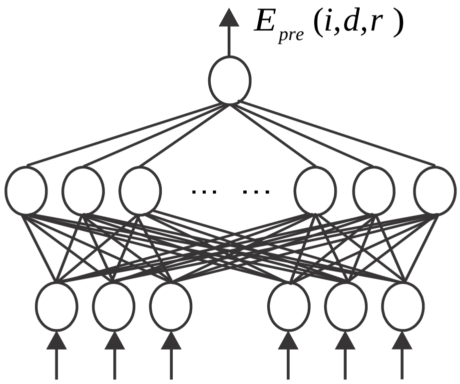

Fig. 5. Neural network based solar energy prediction model.

(BP) algorithm to train the neural network. After trained with data, the neural networks can be used as solar prediction models for all sensor nodes.

B. Cluster Head Selection

Each round of LEACH is divided into two phases, i.e. set-up phase and steady-state phase. Let p be the ratio of the desired number of clusters to the total number of sensor nodes in a network. The optimum number of clusters in a given network can be analytically determined using the computation and communication energy models [7]. In the set-up phase of each round r, each node chooses itself as cluster head by the probability $P(i,r)$ as defined in equation (7), if the node has not been a cluster head in the most recent $1/p$ rounds. Otherwise, the probability is zero.

$$P(i,r) = \frac{p}{1-p\times(r \bmod \frac{1}{p})} \qquad (7)$$

LEACH is designed under the assumption that the energy consumption of being a cluster head is equal for all sensor nodes, but in reality it varies significantly. In addition, LEACH does not take the residual energy and the energy harvesting capability of each node in selecting cluster heads.

For the reasons above, we propose an energy-aware clustering routing algorithm. Its operation is also divided into rounds and each round contains two phases, i.e., set-up phase and steady-state phase. In the set-up phase, the probability of being cluster head is zero for all the sleeping nodes while the probability of each awake node to be cluster head is defined as

$$P(i,d,r) = \frac{p}{1-p\times(r \bmod \frac{1}{p})}\times \frac{\alpha E(i,d,r-1)+\beta E_{pre}(i,d,r)-E_{TX}(k,d_{ibs})}{E_{cap}} \,, \qquad (8)$$

where $E(i,d,r-1)$ and $E_{pre}(i,d,r)$ are the residual energy at the end of round r-1 and the predicted harvested energy during round r in day d for node i, respectively. $E_{pre}(i,d,r)$ can be evaluated using (5) since the relation between the inputs and the output has been learnt by the neural network after the training procedure. d_{ibs} is the distance from node i to the base station. $E_{TX}(k, d_{ibs})$ is the consumed energy for k bits data transmission from node i to the BS, which can be evaluated using (2). E_{cap} is the energy capacity of each node. α and β are coefficients which are used to adjust the contribution of the two factors. Once $P(i,d,r)$ is determined, node i generates a random number between 0 and 1, if the number is lower than $P(i,d,r)$, it will announces itself as a cluster head. Otherwise, it will be treated as non-cluster head node.

C. Cluster Formation

Once the nodes have elected themselves to be cluster heads using the probabilities in (8), the cluster head nodes must let all the other nodes in the network know that they have chosen this role for the current round. To do this, each cluster head node broadcasts an advertisement message (ADV). Each non-cluster head node determines its cluster for this round by choosing the cluster head that requires the minimum communication energy. After each node has decided to which cluster it belongs, it informs the cluster head node that it will be a member of the cluster. The cluster heads then sets up a TDMA schedule and transmits this schedule to the nodes in the cluster. After the TDMA schedule is known by all nodes in the cluster, the set-up phase is complete and the steady-state operation (data transmission) can begin.

Note that nodes in sleeping mode will not join any clusters. They keep sleeping until they wake up, and then wait for a message sent by the base station to start a new round. Once this message is received, they participate in the cluster heads election.

D. Data Transmission

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The steady-state phase is broken into frames, where nodes send their data to the cluster head once per frame during their allocated transmission slot. The cluster head must be

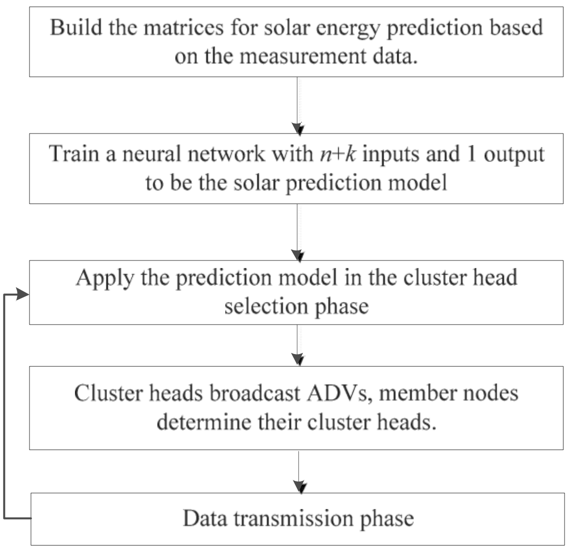

Fig. 6. Flow chart for the proposed routing protocol.

awake to receive all the data, it performs data aggregation to enhance the common signal and reduce the uncorrelated noise among the signals. In this study, we assume that all individual signals can be combined into a single representative signal. The resultant data are then sent from the cluster head to the base station. Since the base station may be far away, this is a high-energy transmission.

The flow chart for the proposed routing protocol is shown in Fig. 6.

IV. EXPERIMENTAL SETUP AND RESULTS

The goal of energy prediction is to predict the solar irradiance using the historical information about this variable. The data was measured each 1 hour, the training set comprises 1440 samples (67% of the total data) and the test set comprises the rest 720 samples (33% of the total data).

The NNtoolbox package of MATLAB is used in the training procedure. Fig. 7 shows the estimation of partial test data using the neural network prediction model. The overall prediction (test) accuracy e_{test} is 12.68%, which can be evaluated using

2

OMNeT++ 4.5 simulator is used to simulate the proposed protocol and LEACH. All 100 nodes are randomly deployed within a 1000 1000 square area while the base station is located at (1500, 750). The data message packet is 500B long. In each round each awake non-cluster head node sends 10 such packets to its cluster head. The control packet is

25B long. The round duration time Δt is 0.1h and the maximum simulation time is set to 72h. α is tuned to be 1.0 and β =2.0. For the energy prediction model, n=3, k=3. A perfect MAC protocol (no interference, no collision) is used with an ideal channel characteristic for simplicity. The initial energy for each node is set to be equal to its capacity. This enables the nodes to perform the first few setup tasks. After that they will rely solely on the energy harvested from

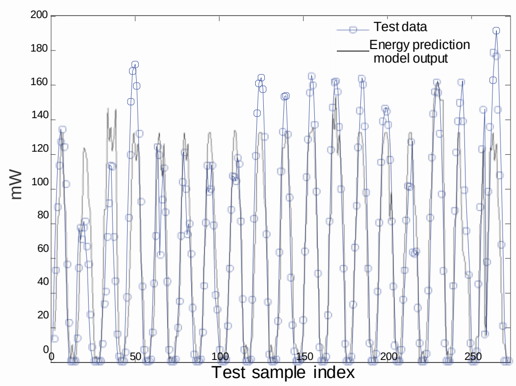

Fig. 7. Solar energy prediction results for partial test data using the neural network predictor.

TABLE I

ENERGY DISSIPATE MODEL PARAMETERS IN SIMULATION

Parameter	Value	Parameter	Value
E_{elec}	50 nJ/bit	E_{mp}	0.0013 pJ/bit/m^4
E_{fs}	10 pJ/bit/m^2	E_{cap}	0.5J

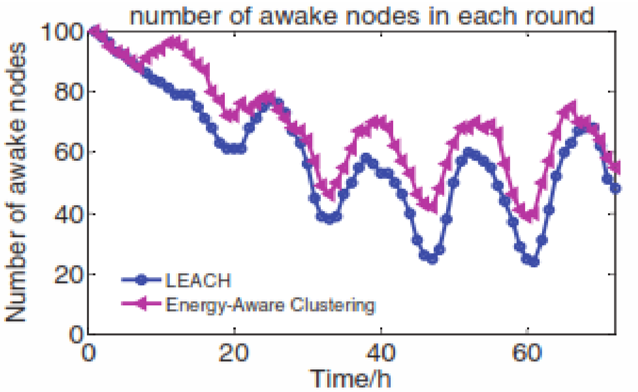

Fig. 8. Number of awake nodes in each round.

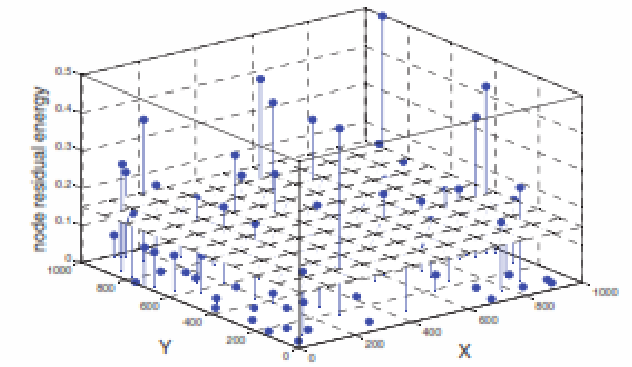

Fig. 9. Node energy status when t=48h for LEACH.

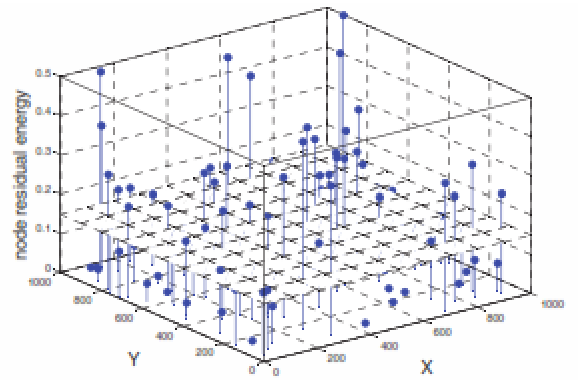

Fig. 10. Node energy status when t=48h for proposed clustering routing.

ambience. Other detailed parameters for radio model are shown in TABLE I.

The number of awake nodes in the EH-WSN is compared for the two routing protocols. The more awake nodes, the more packets will be sent to base station and consequently the more information about the sensed object or environment will be obtained. Fig. 8 compares the number of awake nodes for the two protocols. It can be noticed that the number of awake nodes for the proposed energy-aware clustering routing is consistently larger than that of LEACH. Fig. 9 and Fig.10 show the residual energy status of all nodes when t=48h for the two protocols. The flat surface in the two figures represents the threshold of a node being awake and sleeping. It is obvious that the average residual energy level of nodes for the proposed routing algorithm is greatly higher than that of nodes for LEACH. The number of awake nodes is 48 for energy-aware routing while 28 for LEACH. Fig.11 illustrates the normalized average throughputs of the sensor network with different number of deployed nodes. From it, we can conclude that the proposed clustering routing protocol increases the network throughput by about 30% than LEACH.

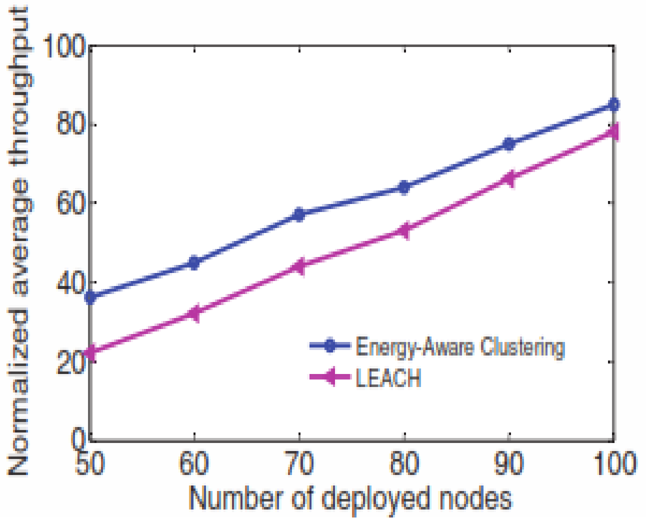

Fig. 11. Normalized average throughputs.

The improvements in number of awake nodes and network throughput are mainly brought in by increasing the probability of nodes with higher energy sustainability to be cluster heads, while decreasing the probability of nodes with poor energy sustainability to become cluster heads. The harvested energy from the ambience is thus used with higher efficiency and the energy consumption among sensor nodes becomes more balanced.

V. CONCLUSION AND FUTURE WORK

We have proposed an energy-aware clustering routing protocol for EH-WSNs. In order to improve the utilization efficiency of the harvested energy, a neural network based solar energy prediction model is exploited to make the routing protocol energy-aware. Nodes with higher residual energy and stronger energy harvesting capabilities have higher probability of being cluster heads. The proposed routing algorithm has stronger ability to balance energy consumption among sensor nodes. In future study, we will be focusing on the dynamic tuning of coefficients α and β to further improve the performance of our proposed algorithm. Moreover, we would try some other kinds of solar energy prediction models to see if we could obtain better prediction accuracy. We might also take the seasonal change in solar irradiance into consideration.

REFERENCES

[1] J. Yick, B. Mukherjee and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, vol. 52, pp.2292-2330, 2008.

[2] E. Lattanzi, E. Regini, A. Acquaviva, and A. Bogliolo, "Energetic sustainability of routing algorithms for energy-harvesting wireless sensor networks," *Computer Communications*, vol. 30, pp. 2976-2986, 2007.

[3] Ongaro, F., Saggini, S., "Li-ion battery-supercapacitor hybrid storage system for a long lifetime, photovoltaic based wireless sensor network", *IEEE Trans. Power Electron.*, 2012, 27, (9), pp. 3944-3952.

[4] Z. A. Eu, H. Tan and W. K. G. Seah, "Opportunistic routing in wireless sensor networks powered by ambient energy harvesting," *Computer Networks*, vol. 54, pp. 2943-2966, 2010.

[5] T. Voigt, H. Ritter, and J. Schiller, "Utilizing Solar Power in Wireless Sensor Networks," in *Proc. oj IEEE Intl Conjerence on Local Computer Networks (LCN)*, Zurich, Switzerland, Oct 20-23 2003, pp. 416-422.

[6] H. C. Chu, W. T. Siao, W. T. Wu, and S. C. Huang, "Design and implementation an energy-aware routing mechanism for solar wireless sensor networks", in *Proc. IEEE Int. Conj. High Perjormance Computing and Communications*, pp. 881-886, 2011.

[7] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks", *IEEE Transactions on Wireless Communications*, vol. I, no. 4, pp. 660--670, 2002.

[8] Meng, J., Zhang, X., Dong, Y., & Lin, X. (2012, August). Adaptive energy-harvesting aware clustering routing protocol for Wireless Sensor Networks. In *Communications and Networking in China (CHINACOM), 2012 7th International ICST Conjerence on* (pp. 742-747).

[9] Xiao, M., Zhang, X., & Dong, Y. (2013, April). An effective routing protocol for energy harvesting wireless sensor networks. In *Wireless Communications and Networking Conjerence (WCNC), 2013 IEEE* (pp. 2080-2084). IEEE.

[10] Wu, Yin, and Wenbo Liu. "Routing protocol based on genetic algorithm for energy harvesting-wireless sensor networks." *Wireless Sensor Systems, IET*3.2 (2013): 112-118.

[11] S. Cao, "Total Daily Solar Irradiance Prediction using Recurrent Neural Networks with Determinants," 2010 Asia-Pacific Power and Energy Engineering Conference (APPEEC), pp. 1-4, 2010.

[12] E. M. Crispim, P. M. Ferreira, A. E. Ruano, "Solar Radiation Prediction Using RBF Neural Networks and Cloudiness Indices," International Joint Conference on Neural Networks (IJCNN '06), pp. 2611 – 2618, 2006.

[13] A. Ghanbarzadeh, A. R. Noghrehabadi, E. Assareh, M. A. Behrang, "Solar Radiation Forecasting Based on Meteorological Data Using Artificial Neural Networks," The seventh IEEE International Conference on Industrial Informatics, pp. 227 – 231, 2009.

[14] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power Management in Energy Harvesting Sensor Networks," *Trans. Embedded Computing Systems*, vol. 6, no. 4, p. 32, 2007.

[15] J. R. Piorno, C. Bergonzini, D. Atienza, and T. S. Rosing, "Prediction and management in energy harvested wireless sensor nodes," in First International Conference on Wireless VITAE, 2009.