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Markov Decision Process Based Switching Algorithm for Sustainable Rechargeable Wireless Sensor Networks

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***Abstract*—In a tree based wireless sensor network, a tree structure rooted at sink node is usually created for efficient data collection. Recently, the use of solar harvesting technologies for rechargeable sensor nodes are evolving. Moreover, in a tree based rechargeable wireless sensor network, the nodes that belong to different routes will have different energy dissipation due to unequal harvested-energy and utilized-energy. Network sustainability and energy efficiency are important issues in a tree based rechargeable sensor network. In this paper, a *Markov Decision Process* based switching algorithm has been designed for a sustainable data collection tree while reducing energy consumption in the network. Further, analysis of energy consumption has been performed using a real-time sensor traffic pattern. A prediction model has been adopted to estimate the harvesting energy (based on solar power) for the rechargeable sensor nodes. In this work, the state of each node is defined based on different independent energy levels. The state of each node may change with time depending on harvested-energy and utilized-energy. The proposed *Markov Decision Process* approach finds the optimal switching policy for sensor nodes which switch from one parent to another based on energy levels to preserve sustainability. A detailed theoretical analysis has been performed along with simulation results to show the efficacy of the proposed approach.**

Keywords*—Rechargeable Wireless Sensor Network; Data collection tree; Markov Decision Process; Switching; Energy harvesting;

I. Introduction

Wireless Sensor Networks (WSNs) consist of a group of sensor nodes which are capable of sensing data (from the environment), such as, temperature, light, humidity, vehicular movement, noise levels, the presence of certain kinds of objects, wind direction and speed [1] [2]. Sensor nodes may have limited energy [1] or energy harvesting [3] [4] capability. In both type of sensors, energy efficiency is an important issue that affects the operation of WSN. To prolong network lifetime, energy harvesting sensor nodes are preferably used over limited battery-powered nodes depending on the availability of energy sources [3]. Rechargeable sensor nodes scavenge energy from surrounding sources, such as, solar, wind, vibrations, and passive human movements [4]. The amount of energy harvested by a sensor node depends on the availability of energy sources (such as sunlight) and also varies according to weather conditions including seasonal changes [5]. In a rechargeable WSN, a sensor survives till the next recharge schedule to protect the network from partitioning. Further, once a rechargeable sensor node exhaust its energy, it may join the network again after the next recharge schedule. In this paper, a solar-powered *Rechargeable Wireless Sensor Network* (RWSN) is considered to design a sustainable data sensing paradigm.

In a rechargeable WSN, the sustainability of the network is an important issue to improve the overall lifetime of the network. Moreover, in a typical non-rechargeable tree-structured WSN, sensor nodes forward sensed data to a central sink using a data collection tree [6]. A data collection tree gets partitioned once an intermediate node exhaust its energy. The lifetime of such a network can be improved by balancing the energy consumption of sensor nodes. In [6], the problem of lifetime maximization of WSN is presented in the context of data collection trees. However, for a rechargeable WSN, the survivability of sensor nodes till the next recharge schedule is a major concern to prolong the network lifetime. Further, real-time network traffic-load and different states (in terms of residual energy levels) of energy harvesting sensors are not considered in [6] to compute the energy consumptions of sensor nodes. Therefore, energy efficiency of rechargeable sensor nodes with varying energy levels need to be analyzed for designing an adaptive load balancing algorithm to provide network sustainability. Moreover, during data acquisition, nodes deplete their energy while performing operations such as sensing, transmitting and receiving. The sensor nodes should choose their operations adaptively to prolong network lifetime. Further, the data collection tree need to be balanced due to unequal energy dissipation and available harvesting resources.

In this work, a *Markov Decision Process* (MDP) based load balancing technique has been designed with varying the energy levels of sensor nodes while choosing the operation of sensor nodes adaptively according to residual energy. Using the proposed algorithm, a node chooses the operations (sensing, transmitting and receiving) adaptively to sustain till the next recharge schedule (cycle) in the network. Energy consumptions have been estimated using real-time network traffic with various sensor operations. A prediction algorithm has been adopted to analyze the amount of harvested energy in a rechargeable

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WSN. The energy levels of sensors are provided as inputs to the MDP algorithm. The proposed algorithm selects the optimal policy and takes energy balancing (switching) decision based on the residual energy of each node. An energy-balanced network is generated when the energy consumption of sensors adaptively changes based on harvesting energy sources and network traffic loads. To the best of our knowledge, this is the first work which proposes a MDP algorithm to improve lifetime for a sustainable rechargeable WSN.

The major contributions of this work are as follows:

- Design of an energy model by considering real-time network traffic with various sensor operations (sensing, transmitting and receiving) and energy harvested sensor nodes in a tree based wireless sensor network.
- Design of a *Markov Decision Process* (MDP) based switching algorithm to improve lifetime and to achieve a sustainable data collection tree.
- Simulations results are presented to show the efficacy of the proposed MDP algorithm with *real-time* network traffic.

II. Related Work and Motivation

In this section, existing works on lifetime, energy efficiency and energy harvesting have been discussed. In [7] and [8] energy consumption models have been proposed including analysis of lifetime of sensor network.

Energy conservation schemes have been proposed to extend network lifetime by Anastasi *et al.* [9]. In [10], a cluster based duty cycled wireless sensor network has been considered and network coding based data aggregation strategy has been proposed. A load balancing based randomized switching algorithm has been proposed for maximizing lifetime in the context of data collection trees by Imon *et al.* [6]. A probabilistic model for estimating the lifetime of wireless sensor network has been presented in [11]. Rout *et al.* [12] have estimated the lifetime of WSN using duty cycle and network coding. However, in our work, we have designed an energy utilization model to estimate the residual energy of a node in a rechargeable tree based sensor network.

Tashtarian *et al.* [13] have proposed a solution to obtain the trajectory of mobile sink which increases the network lifetime. To improve the lifetime, a mobile sink based energy efficient clustering protocol has been proposed by Abo-Zahhad *et al.* [14]. In [15], a genetic algorithm based self-clustering method has been presented to optimize the network lifetime. A network coding based probabilistic routing for clustered WSN has been presented by Rout *et al.* [16]. Abd *et al.* [17] have proposed a game theoretic energy balance routing protocol to address load balance problem. An energy-balanced routing method has been proposed by Zhang *et al.* [18]. Tunca *et al.* [19] have proposed a distributed energy-efficient mobile sink routing protocol.

To address the lifetime maximization problem in WSN, Yang *et al.* [20] have proposed algorithms for complete target coverages for energy harvesting sensor nodes. Dynamic activation of sensor nodes to maximize system performance has been presented by Kar *et al.* [21]. A markovian model has been used for calculating sensor discharge and recharge periods. Active time scheduling protocols are proposed for rechargeable sensor network by Pryyma *et al.* [22]. Dynamic activation policies for event capture in rechargeable sensor network have been proposed by Ren *et al.* [23].

Markov Decision Process has been adopted to improve the performance of *Wireless Sensor Networks* in various applications [24]. *Markov Decision Process* based analysis has been done for rechargeable nodes by Misra *et al.* [25]. A MDP model based censoring policy has been proposed for energy efficient transmission in harvesting sensor nodes [26]. In [27], a *Markov* model has been presented for energy harvesting nodes. In [28], *Markov Decision Process* based policies are designed for optimal data transmission and battery recharging for solar powered sensor nodes. In our work, we have designed a *Markov Decision Process* based switching algorithm to determine the optimal policy which provides the sustainability of a data collection tree.

In [29], an exponential weighted moving average model has been proposed to find out the diurnal cycle in solar energy including seasonal variations. In advanced expectation model [30], a parameter related to the actual amount of harvested energy has been introduced and it addresses the temporal environmental conditions. A weather condition moving average model has been proposed in [5]. Weather-conditioned selective moving average model has been proposed by Jiang *et al.* [31] using the trend similarity of energy harvesting and classification of sunny and cloudy days. An additive decomposition model based solar energy prediction algorithm has been proposed in [32]. The profile energy prediction model proposed in [33] estimates the future energy availability for solar and wind harvesting WSN.

A. Motivation and Problem Formulation

In [6], a randomized switching algorithm has been proposed for balancing the data collection tree so that all nodes have uniform load in terms of data forwarding. However, in [6], limited battery powered sensor nodes are considered. Moreover, in a tree based rechargeable WSN, the nodes that belong to different routes will have different energy dissipation due to unequal harvested-energy and utilized-energy. In this paper, solar powered rechargeable sensor nodes are considered. The amount of harvested energy depends on the availability of sunlight. Solar harvesting sensor nodes are having different energy levels based on the amount of energy harvested by the nodes. If a node is not having sustainable energy till the next recharge cycle, it uses stored energy optimally and reduces its energy consumption by reducing operations (like switch off the receiver and transmitter). In this case, node's children switch to some other parent and forward the data through the new parent. The focus of this work is to estimate the energy consumption of energy harvesting nodes in a tree based WSN and to design a *Markov Decision Process* based switching method to achieve sustainability in rechargeable WSN.

The rest of the paper is organized as follows. In section III, the energy utilization model has been presented in a tree based rechargeable WSN. In section IV, a *Markov Decision Process* based switching algorithm has been presented to provide network sustainability. Performance evaluation has been

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done through simulation results in section V. The concluding remarks are given in section VI.

III. Estimation of Energy Utilization

In this section, a network model has been introduced. An energy consumption model has been presented to estimate energy utilization in the network. Further, an energy harvesting model has been presented for predicting harvested energy.

A. System Model and Assumptions

$G(N, E)$ be a graph representing n sensor nodes which are placed randomly, where $N = \{v_0, v_1, ..., v_n\}$ denotes a set of vertices and v_0 denotes sink node. The set of communication links are represented by E. $T(N_T, E_T)$ is a data collection tree which represents an acyclic spanning subgraph of G with $N_T = N$ and $E_T \subseteq E$, where v_0 is the root of T. The residual (current) energy budget of v_i is referred to as re_i. Total energy consumption of a node is represented by ce_i. In each *data collection round*, sink node collects data from all sensor nodes [6] [34]. In this paper, data collection round is also denoted as *round*. Path energy (pr_i) of a node v_i is the minimum residual energy of all nodes along the path from v_i to v_0. The path energy balancing parameter $p(r)$ is defined as the difference between *max*$\{pr_i^L\}$ and *min*$\{pr_i^L\}$, where pr_i^L denotes the set of path energies of all leaf nodes i.e., $pr_i^L = \{pr_i | v_i \in L\}$, L is the set of leaf nodes in data collection tree.

B. Energy Consumption Model

In this section, we analyze energy consumptions for the proposed network model (as discussed in section III-A). A binary sensor tree is defined with height h. The energy consumptions of the tree is determined level wise by using the model as described in [7]. E_{sense}, E_{rx} and E_{tx} are the energy consumptions by a sensor node in sensing, receiving and transmitting data over a distance d, respectively. A path loss model (with path-loss exponent $\widehat{n}$) has been considered where signal strength reduces by $\frac{1}{d^{\widehat{n}}}$. Here, d is the distance of separation between the sender and receiver node [7]. The energy consumptions [7] are given by $E_{sense} = \alpha_3$, $E_{rx} = \alpha_{12}$, $E_{tx} = \alpha_{11} + \alpha_2 d^{\widehat{n}}$, where α_{11}: energy consumption per bit by the transmitter electronics, α_2: energy dissipation in the transmit *op-amp*, α_{12}: energy consumption per bit by the receiver electronics and α_3 is the energy consumption for sensing a bit. The energy consumptions are estimated by considering an event-centric application [35] [10]. Assume, l is the size of generated data by each sensor node per event. The average rate at which events occur per unit time is β [8]. Therefore, energy consumption for sensing till time t is represented as $\alpha_3 lt\beta$.

1) Energy Consumption of a node in a sensor tree: Energy consumption of a node in sensor tree is analyzed by assuming that number of children of a node v_i is C_i. Energy consumption of a node v_i for receiving data from its children is $\alpha_{12} C_i lt\beta$. Total energy consumption (ce_i) of a node (say v_i) is given by

$$\begin{aligned} ce_i &= \alpha_3 lt\beta + \alpha_{12} C_i lt\beta + (C_i lt\beta + lt\beta)(\alpha_{11} + \alpha_2 d^{\widehat{n}}) \\ &= lt\beta[\alpha_3 + \alpha_{12} C_i + (C_i + 1)(\alpha_{11} + \alpha_2 d^{\widehat{n}})] \end{aligned} \quad (1)$$

First term in *Equation* (1) is the energy consumption for sensing till time t. Energy consumption for receiving children data is represented by second term in *Equation* (1) and last term signifies the energy consumption for transmitting the total data (i.e sensed and received data).

2) Energy Consumption of leaf level (E_{lf}): Energy consumption of a node in leaf level is equal to the sum of the energy consumptions for sensing data and forwarding the data. The generated data will be transmitted through multi-hop path to the sink. So, the energy spent by each leaf level node till time t is given by $[\alpha_3 lt\beta + (\alpha_{11} + \alpha_2 d^{\widehat{n}}) lt\beta]$. In the proposed network model, the number of nodes at leaf level is 2^h. Hence, the total energy consumption at leaf level is given by

$$E_{lf} = 2^h[\alpha_3 lt\beta + (\alpha_{11} + \alpha_2 d^{\widehat{n}}) lt\beta] \quad (2)$$

First term in *Equation* (2) is the energy consumption of leaf level nodes for sensing till time t. Second term in *Equation* (2) represents the energy consumption for transmission of sensed data.

3) Energy Consumption at level k (E_k): The energy consumption at level k is sum of energy consumptions for (a) sensing (b) transmitting its own sensed data and (c) relaying data received from its children. The energy consumption E_k is

$$\begin{aligned} E_k &= 2^k[\alpha_3 lt\beta + (\alpha_{11} + \alpha_2 d^{\widehat{n}}) lt\beta] \\ &\quad + (2^{h+1} - 2^{k+1})(\alpha_1 + \alpha_2 d^{\widehat{n}}) lt\beta \\ &= lt\beta[2^k(\alpha_3 + \alpha_{11} + \alpha_2 d^{\widehat{n}}) + (2^{h+1} - 2^{k+1})(\alpha_1 + \alpha_2 d^{\widehat{n}})] \end{aligned} \quad (3)$$

where, $\alpha_1 = \alpha_{11} + \alpha_{12}$. The maximum energy consumption (E_{bt}) of a binary sensor tree is given by

$$E_{bt} = \sum_{k=0}^{h} [lt\beta[2^k(\alpha_3 + \alpha_{11} + \alpha_2 d^{\widehat{n}}) + (2^{h+1} - 2^{k+1})(\alpha_1 + \alpha_2 d^{\widehat{n}})]] \quad (4)$$

Therefore, maximum energy consumption for $\overline{n}$-ary sensor tree (*i.e.* every node in $\overline{n}$-ary sensor tree is having maximum of $\overline{n}$ children) is given by $E_{\overline{n}t}$

$$E_{\overline{n}t} = \sum_{k=0}^{h} [lt\beta[\overline{n}^k(\alpha_3 + \alpha_{11} + \alpha_2 d^{\widehat{n}}) + (\overline{n}^{h+1} - \overline{n}^{k+1})(\alpha_1 + \alpha_2 d^{\widehat{n}})]] \quad (5)$$

C. Energy Harvesting Model

In our work, solar powered sensor nodes are considered based on a *Weather Conditioned Moving Average* model [5]. The model is used for predicting the harvested energy using solar sensors. Energy prediction is required for making decisions for the future time slots in the proposed switching method (as discussed in section IV). The future energy available to the system can be predicted by using past history. However, sudden changes in weather conditions and seasonal variations also affect the amount of harvested energy. In our system model, a day is divided into q time slots such as $\{t_0, t_1, ..., t_q\}$ and $pe(d, t)$ represents the predicted harvested energy for a day d at time slot t. As per model [5], the predicted value is related to the previous slot value in the same day and the mean value

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of the past days of same slot. The amount of energy harvested at the next time slot is estimated by using following equation:

$$pe(d,t+1) = \alpha.pe(d,t) + GAP_k.(1-\alpha).M_D(d,t+1) \quad (6)$$

where, α is a weighting factor and $M_D(d,t+1)$ is the mean of the harvesting energies at $(t+1)$ time slots for the previous D days. The solar conditions in the present day relative to previous days is measured by using GAP_k factor [5].

The residual energy (re^{t+1}) at next time slot $(t+1)$ is estimated by using the following formula:

$$re^{t+1} = re^t + pe(d,t+1) - ce^{t+1} \quad (7)$$

where, ce^{t+1} is the energy consumption of a node at time slot $(t+1)$ and it is determined by using *Equation* (1). Nodes may have different energy levels because of heterogeneity in harvesting energy sources, which may vary at different interval of time. In this work, the states of the sensor nodes are categorized into s different states, such as, S_1, S_2.....S_s, according to energy levels.

In the next section, a *Markov Decision Process* based energy balancing algorithm is proposed. Equation (7) (for estimating the residual energy) is used in the proposed algorithm for energy balancing.

IV. Markov Decision Process Based Switching Algorithm

In this section, a *Markov Decision Process (MDP)* based switching algorithm (*Algorithm 1*) has been presented. The proposed MDP based approach have five major functions, such as, *MDP_SWITCH()*, *MDP()*, *FIND_RES_ENERGY()*, *FIND_ENERGY_CONSUMP()* and *FIND_POT_PARENTS()*. The *FIND_RES_ENERGY()* and *FIND_ENERGY_CONSUMP()* functions return the residual energy of a node and energy consumption of a node, respectively. The *FIND_POT_PARENTS()* function is used to select the potential parent for a node which is selected for switching. Function *MDP()* returns the switching decision of the *Markov Decision Process* and *MDP_SWITCH()* switches the children to respective potential parents.

The data collection tree (T), as discussed in Section III-A, is the input to the *Algorithm 1*. The function *FIND_RES_ENERGY()* is called at time slot t and it returns the residual energy of a node v_i at time slot $(t+1)$, as shown in *Algorithm 2*. The term pe^t (in line 1, Algorithm 2) is the predicted harvested energy (which is estimated using *Equation* (7)) of a node at time slot t. The *FIND_ENERGY_CONSUMP*(v_i,t) function (*Algorithm 3*) estimates the energy consumption (ce_i) of a node v_i in a given time slot t using *Equation* (1).

In time slot t, a node v_i (*Algorithm 1*) is initialized with residual energy re_i^t. A node determines the residual energy in time slot $(t+1)$ using *Algorithm 2*. The energy consumption of a node at time slot $(t+2)$ is estimated using *Algorithm 3* (refer line 3, *Algorithm 1*).

After each data collection round, the nodes which are not having sustainable energy for the next time slot are selected (refer line 5, *Algorithm 1*). For all selected nodes, *MDP()* returns the switching decision, on the basis of the residual energy as shown in *Algorithm 4*. Reward for each policy is determined (line 4, *Algorithm 4*) and the optimized policy is selected (line 6, *Algorithm 4*) by the nodes. If switching decision is true (line 7, *Algorithm 4*), then the function *FIND_POT_PARENTS()* (*Algorithm 5*), is invoked by all the children of the selected nodes and it returns the potential parents. Potential parents are the nodes which are having connection link with the selected nodes and having sustainable energy for the next time slot (line 2, *Algorithm 5*). Among the potential parents, the maximum residual energy node (v_p) is selected as a new parent (line 13, *Algorithm 1*). Further, the node is switched to new parent and the tree is updated (line 14, *Algorithm 4*). Further, every node will discover its parent and children using the tree update operation. The proposed switching operation provides sustainability to the tree-based rechargeable WSN and the network lifetime will be improved. In the next section, *Algorithm 4* is explained with a case study.

Algorithm 1 MDP_SWITCH(T)

1: Initialize (re_i^t) for each $v_i \in V$
2: re_i^{t+1} = FIND_RES_ENERGY$(v_i, t+1, re_i^t)$ for each $v_i \in V$;// (after each data collection round)
3: ce_i^{t+2} = FIND_ENERGY_CONSUMP$(v_i, t+2)$ for each $v_i \in V$;
4: **for** $i = 1$ to n **do**
5:     **if** $re_i^{t+1} \geq ce_i^{t+2}$ **then** go to 4;
6:     **else**
7:         **if** MDP(re_i^{t+1}) == false **then** go to 4;
8:         **else**
9:             Enqueue(children(v_i));
10:             **while** IsEmptyQueue == false **do**
11:                 v_j = Dequeue();
12:                 W = FIND_POT_PARENTS(G,v_j);
13:                 $\forall v_i \in W$ find the node v_p with $\max(re_i^{t+1})$;// v_p is new parent of v_j
14:                 Update the tree
15:             **end while**
16:         **end if**
17:     **end if**
18: **end for**
19: go to 2;

Algorithm 2 FIND_RES_ENERGY(v_i,t,r)

1: Get the value of pe^t;
2: ce_i^t = FIND_ENERGY_CONSUMP(v_i,t);
3: calculate re_i^{t+1} = r + pe^t - ce_i^t;
4: **return** re_i^{t+1};

A. Illustrative Case Study

In this section, *Algorithm 1* has been illustrated with the help of a case study as shown in Fig. 1. Fig. 1 shows a data collection tree, where solid lines indicate the edges in the

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Algorithm 3 FIND_ENERGY_CONSUMP(v_i, t)

Find number of children C_i
Set values of $\alpha_3, \alpha_{11}, \alpha_{12}, \alpha_2, l, t, \beta$;
Calculate ce_i = $lt\beta[\alpha_3$ + $\alpha_{12}C_i$ + $(C_i$ + 1$)(\alpha_{11}$ + α_2 $d^{\widehat{n}})]$;
return ce_i;

Algorithm 4 MDP(re_i)

Find out state S_i of the node v_i by re_i
for All MDP switching policies find reward **do**
    Find steady state probabilities Π_1, Π_2, Π_3....Π_s where s is the number of states(probability values will be calculated by transition probability matrix of each policy)
    Reward = Π_1 R_1 + Π_2 R_2 + Π_3 R_3 + ...+ Π_s R_s where R_1,R_2...R_s are rewards in each state
end for
Select the optimized policy
Check the decision for the state of the node in policy
if decision is to switch off the receiver **then return** true; //node's children switch because receiver is off
else
    return false;
end if

current tree and the dotted lines represent potential edges that can be used to realize a new sustainable tree. For analytical results, the energy parameters are considered as per MICA mote sensors [36]. The energy consumption parameters are as follows: Number of nodes = 7, Initial energy budget = 2500 Joules, $\alpha_{11} = 0.937 \times 10^{-6}$ Joules/bit, $\alpha_{12} = 0.787 \times 10^{-6}$ Joules/bit [10], $\alpha_2 = 10 \times 10^{-12}$ Joules/bit, $\alpha_3 = 50 \times 10^{-9}$ Joules/bit, d = 85 m and path loss component $(\widehat{n})$ is 2 [7]. Data generated by each node per event (i.e. l) is 960 bits [10] and all the nodes are having different values of β. To compute harvested energy, the day is divided into 24 time slots and each time slot is of one hour. There is one data collection round at each hour. Solar energy is available for 12 hours during day time and it is not available during night time. Here, *day 1* is considered as sunny day and *day 2* is considered as cloudy. The values of solar harvested energy for different time slots of a day are considered according to existing *WCMA* model [5].

The residual energy of all the nodes is determined at future time slot by using *Equation* (7). The *Equation* (7) uses re^t (i.e. residual energy at time slot t), $pe(d, t+1)$ (i.e. the predicted harvested energy for time slot $(t+1)$ is estimated using *Equation* (6)) and ce^{t+1} (i.e. the energy consumption for $(t+1)$ time slot is estimated using *Equation* (1)). Table I shows the energy consumptions and residual energy for each node after 29 data collection rounds.

Algorithm 5 FIND_POT_PARENTS(G,v_j)

for $\forall v_k$ that are neighbors of v_j in G **do**
    if $(re_k^{t+1} \geq ce_k^{t+2})$ **then** $W = W \cup \{v_k\}$;//Initial value of potential parent W is Null
    end if
end for
return W;

TABLE I: Energy Consumption and Residual Energy of nodes

Nodes	β	Sensing (Joules)	Receiving (Joules)	Transmitting (Joules)	Total (Joules)	Residual Energy (Joules)
1	500	1.44	47.5978	90.10	139.14	134.55
2	50	0.144	0	2.90	3.05	2448.14
3	300	0.864	0	17.43	18.30	2188.83
4	300	0.864	20.39	43.59	64.86	1397.34
5	250	0.72	0	14.53	15.25	2240.7
6	200	0.576	0	11.62	12.20	2292.56

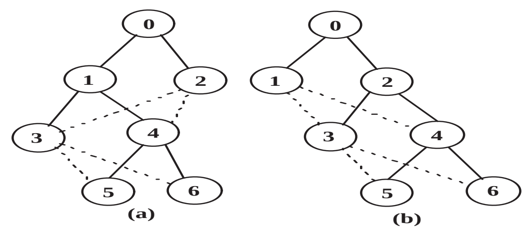

Fig. 1: (a) Tree before switching (To conserve energy, node 1 switch off (turn off) its receiver) (b) Tree after switching (Node 3 and node 4 are switched to node 2).

As shown in Table I, the residual energy (i.e. 134.55 Joules) for node 1 in the next time slot is less than the required total energy consumption (139.14 Joules). According to the line 5 of *Algorithm 1*, node 1 is selected for running MDP() (*Algorithm 4*).

1) Markov Decision Process based analysis of policies: In this section, policies, decisions and actions of the proposed MDP based approach have been presented. According to *Markov Theory*, the future state of a sensor node depends upon the current state rather than the past state. In this work, five different energy states are defined and considered based on energy levels. State S_5 is having maximum energy (level 5) and state S_1 is having minimum energy (level 1). Let, the set $\{Y_0$, Y_1, $Y_2, ...\}$ represents number of residual energy units a sensor node has at $\{0^{th}$, 1^{st}, $2^{nd}, ...\}$ time slots. $P\{Y_{t+1} = j|Y_t = i\}$ is the probability that a node is having i units of residual energy at time t and it will have j units of residual energy at time interval $(t+1)$. Here, $\{c_0$, c_1, c_2,...$\}$ are the number of units of residual energy consumed during $\{0^{th}$, 1^{st}, $2^{nd}, ...\}$ time slots and so on. Therefore, the random variable c_t is the units of residual energy consumed in time interval t. It is assumed that c_t follows a Poisson distribution with mean (λ) one unit of residual energy [25]. Thus, the over all scenario can be represented as a MDP.

$$f(c_{t+1} = k) = (\lambda^k e^{-\lambda})/k! \quad (8)$$

Thus, Y_t (for $t = 0, 1, 2, ...$) is a stochastic process. The possible states of a node at a given time slot are S_5 with a total residual energy capacity of 5 units, S_4 with a residual

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TABLE II: Initial Transition Matrix with $pe^{t+1} = 2$ units

P_{ij}	S_5	S_4	S_3	S_2	S_1
S_5	0.368	0.368	0.184	0.061	0.019
S_4	0.368	0.184	0.061	0.019	0.003
S_3	0.368	0.368	0.184	0.061	0.019
S_2	0	0.368	0.368	0.184	0.061
S_1	0	0	0.368	0.368	0.184

energy capacity of 4 units, S_3 with a residual energy capacity of 3 units, S_2 with a residual energy capacity of 2 units and S_1 with a residual energy capacity of one unit. The amount of harvested energy by a sensor node at time $(t + 1)$ is pe^{t+1} as per WCMA model [5] and it is converted to residual energy units. The value of c_{t+1} is calculated for the transition from Y_t to Y_{t+1} by the following:

$$Y_{t+1} = \begin{cases} max\{5 - c_{t+1}, 1\}, & \text{if } Y_t = 5, \\ max\{Y_t - c_{t+1} + pe^{t+1}, 1\}, & \text{if } Y_t \leq 4. \end{cases}$$

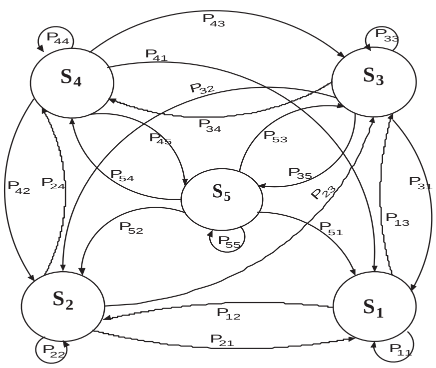

Fig. 2: State Transition Diagram

The probability value P_{ij} for transition from Y_t to Y_{t+1} is calculated by putting this value of c_{t+1} in *Equation* (8). Table II shows initial transition matrix and Fig. 2 shows the state transition diagram where S_5, S_4, S_3, S_2 and S_1 are the states of the node and P_{ij} is the probability of transition from state S_i to S_j. The maximum amount of harvesting energy is considered as 2 units.

In the case study(refer Fig. 1), for data collection round 30, the harvested energy is assumed as 0 (zero) and Table III shows the initial transition matrix for a node with $pe^{t+1} = 0$.

The energy conservation of the nodes is considered as reward of the MDP policy. Sensor nodes consume energy during performing operations. If the node is having more energy, it performs more operations and if it is having less energy, it reduces operations, like, switch off receiver or transmitter to conserve energy. Therefore, energy conservation of a node is inversely proportional to the residual energy of the node as shown in the following equation.

TABLE III: Initial Transition Matrix for given case study

P_{ij}	S_5	S_4	S_3	S_2	S_1
S_5	0.368	0.368	0.184	0.061	0.019
S_4	0	0.368	0.368	0.184	0.08
S_3	0	0	0.368	0.368	0.264
S_2	0	0	0	0.368	0.632
S_1	0	0	0	0	1

TABLE IV: Expected energy conservation

State	Residual energy(in units)	Energy conservation
S_5	5	0.2 μ
S_4	4	0.25 μ
S_3	3	0.33 μ
S_2	2	0.5 μ
S_1	1	1 μ

$$\text{Energy conservation} = \mu \frac{1}{\text{Residual energy}} \tag{9}$$

where, μ is constant. The expected energy conservation is estimated by using the *Equation* (9) as shown in Table IV.

Three decisions have been considered for MDP as shown in Table V. *Decision 1* is *Do nothing*, where a node will not reduce any of its current operations. *Decision 2* is *Receiver off* and *transmitter on*, where the node stops receiving data and the data of the sub-tree will be lost. So, switching should take place and the children of that node should be switched to some other healthy nodes (in terms of residual energy) to achieve a sustainable tree. This switching operation protects the tree from partitioning. *Decision 3* is *Receiver off and transmitter off*, where the node switches off receiver and transmitter. Further, switching decision is also take place at this state.

Table VI shows policies and decisions for each state. For simplicity, we have considered two policies. The first policy is, *Not to receive* (i.e. switch off receiver), if the node is in state S_1, S_2, S_3 (based on policy RP_{123} as shown in Table VI). In table VI, all other states(i.e. S_4, S_5) the decision is *Do nothing*. Table VII shows the transition probability matrix for policy RP_{123}. Second policy is *Not to receive*, if the node is in state S_1, S_2 (RP_{12}). In this case, if the node is in state S_1 or S_2, then it switches off its receiver. Table VIII shows the transition probability matrix for policy RP_{12}.

Expected energy conservation is called as reward and is

TABLE V: Decisions and actions

Decision	Action
1	Do nothing
2	Receiver off and Transmitter on
3	Receiver off and Transmitter off

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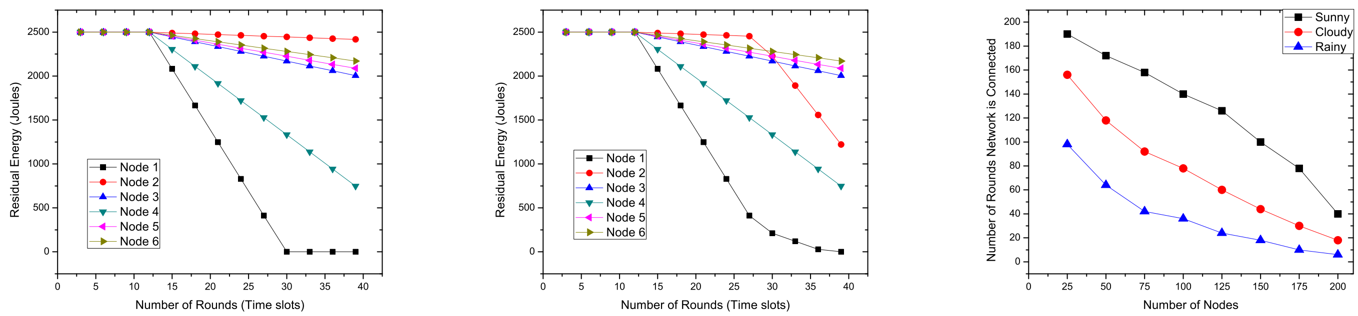


(a) (b) (c)

Fig. 3: Residual energy of the nodes (a) without proposed algorithm (b) with proposed algorithm (c) Number of data collection rounds network is connected in different weather conditions

TABLE VI: Policies

Policy	Verbal description	D_5	D_4	D_3	D_2	D_1
RP_1	Switch off Receiver if state is S_1	1	1	1	1	2
RP_{12}	Switch off Receiver if state is S_1,S_2	1	1	1	2	2
RP_{123}	Switch off Receiver if state is S_1,S_2,S_3	1	1	2	2	2
RP_{234}	Switch off Receiver if state is S_2,S_3,S_4	1	2	2	2	1
RTP_1	Switch off Receiver and transmitter if state is S_1	1	1	1	1	3
RTP_{12}	Switch off Receiver and transmitter if state is S_1,S_2	1	1	1	3	3

TABLE VII: The Transition matrix for policy RP_{123}

P_{ij}	S_5	S_4	S_3	S_2	S_1
S_5	0.368	0.368	0.184	0.061	0.019
S_4	0	0.368	0.368	0.184	0.08
S_3	0	0.216	0.784	0	0
S_2	0	0	0.216	0.784	0
S_1	0	0	0	0.216	0.784

TABLE VIII: The Transition matrix for policy RP_{12}

P_{ij}	S_5	S_4	S_3	S_2	S_1
S_5	0.368	0.368	0.184	0.061	0.019
S_4	0	0.368	0.368	0.184	0.08
S_3	0	0	0.368	0.368	0.264
S_2	0	0	0.216	0.784	0
S_1	0	0	0	0.216	0.784

TABLE IX: Policies and rewards

Policy	Π_1	Π_2	Π_3	Π_4	Π_5	Reward
RP_{123}	0.067	0.2212	0.530	0.1812	0	0.3887μ
RP_{12}	0.236	0.568	0.194	0	0	0.584μ

calculated by using the equation as shown below:

$$\sum_{k=1}^{s}[\Pi_k R_k] \tag{10}$$

where, Π_k is the steady state probability and it is calculated using transition probability matrix (Table VII for RP_{123} and Table VIII for policy RP_{12}). R_k is the expected energy conservation (refer Table IV) of a node and s is the number of states.

Policy RP_{12} is selected to give maximum reward as shown in Table IX. In the given case study, according to energy levels, node 1 is in state S_1. According to policy RP_{12} as shown in Table VI, decision for state S_1 (i.e. D_1) is 2. *Decision 2* is to *switch off the receiver*, as shown in Table V. If the node 1 is switching off the receiver, the MDP() function returns switching decision as *true* (line 8, *Algorithm 4*). Now, *FIND_POT_PARENT(G,v_j)* is called to find out the potential parents for node 3 and node 4. In Fig. 1, the dotted lines shows that node 2 is a potential parent and also it is having sustainable energy for the next time slot. Therefore, node 3 and node 4 are switched to node 2. Fig. 1(b) shows the tree after switching. If the switching is not there, node 1 depletes all its energy and can not sustain for next time slot. Hence, data of left sub-tree will not reach to sink node and the network will be partitioned. However, using the proposed switching algorithm, node 3 and node 4 forward data through node 2 to the sink. Thus, the MDP based switching method provides sustainability to the network and improves the network lifetime.

Fig. 3(a) shows the residual energy of the nodes without the proposed switching algorithm. After 29 rounds, node 1 depletes all its energy and the network is disconnected. Fig. 3(b) shows the residual energy using the proposed algorithm. Node 1 sustains up-to 36 rounds and the network sustainability is improved up-to 7 rounds.

B. Analysis of MDP based switching algorithm

In this section, we have analyzed the time complexity of proposed MDP based switching algorithm. Initialization of residual energy for all nodes at time slot t takes $O(n)$ time in MDP_SWITCH function (line 1, *Algorithm 1*). *Algorithm 3* takes $O(\widehat{g}_{max})$ time, where $\widehat{g}_{max}$ is maximum number of children of a node in the tree. Residual energy of a node at particular time t is computed by *Algorithm 2*. The running time of *Algorithm 2* is $O(\widehat{g}_{max})$. In *Algorithm 1*, line 2 and line 3 run using $O(n\widehat{g}_{max})$ time. The loop on line 4 runs for all nodes in the network. Line 5 requires $O(1)$ time. In line 7, MDP function (*Algorithm 4*) runs in $O(1)$ time. Line 9 takes $O(\widehat{g}_{max})$ time. The inner loop on line 10 runs for $O(\widehat{g}_{max})$ time. FIND_POT_PARENTS() function (*Algorithm 5*) on line 12 takes $O(\widehat{p}_{max})$ time, where $\widehat{p}_{max}$ is the maximum number of neighbors of a node in the connectivity graph G. The operation *Update the tree* on line 14 takes $O(n)$ time. The inner loop (from line 10 to line 15) runs in $O(n\widehat{g}_{max})$ time. Since $\widehat{g}_{max} \leq \widehat{p}_{max} < n$, the total time complexity of MDP based switching algorithm is obtained as $O(n^2\widehat{g}_{max})$.

V. Performance Evaluation

This section presents the evaluation of proposed MDP based algorithm compared with randomized algorithm [6] in terms of network connection statistics, such as, number of data collection rounds in which the network is connected, first node disconnection round and path energy balancing parameter. Network simulator-3 [37] has been used for simulation of proposed algorithm.

A. Experimental Setup

The sensor nodes are placed randomly in the deployment area and network is created in the form of graph. An initial data collection tree, rooted at the sink node, is constructed by using breadth-first-search algorithm. In each data collection round, a node relays the data (sensed data and received data) to its parent. Here, the sink is not an energy-constrained node.

Simulation parameters are considered as follows: deployment area is 200×200 m^2, radio transmission range is set to 30 m, the minimum distance between any two sensor nodes is set to 5 m and the initial energy of a node is 2500 Joules. The energy consumption parameters are considered as MICA mote specifications [36] as follows: $\alpha_{11} = 0.937 \times 10^{-6}$ Joules/bit, $\alpha_{12} = 0.787 \times 10^{-6}$ Joules/bit [10], $\alpha_2 = 10 \times 10^{-12}$ Joules/bit, $\alpha_3 = 50 \times 10^{-9}$ Joules/bit, $d = 85$ m, $\widehat{n} = 2$ [7]. The value of l is considered as 960 bits [10] and the value of β is considered as 100. The harvested energy consumption is computed based on the parameters as mentioned in IV-A.

B. Simulation Results

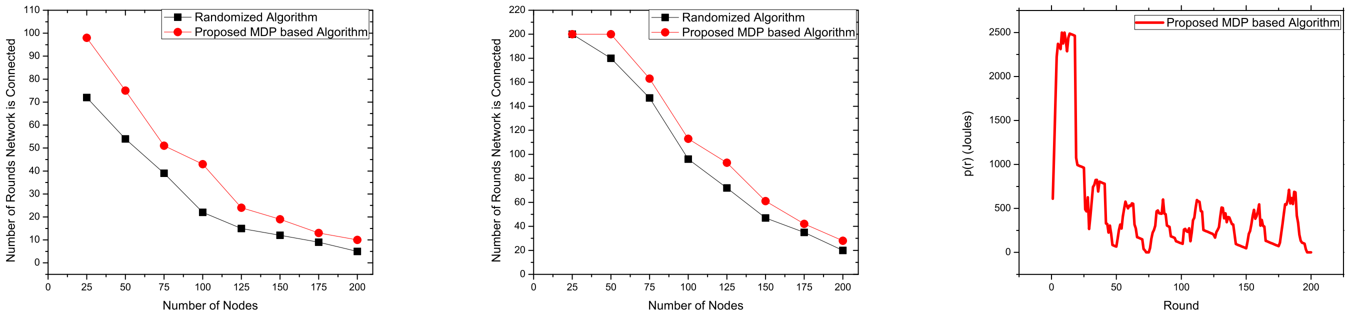
In this section, two scenarios are considered for performance analysis of the proposed MDP based algorithm. In the *first scenario* (scenario 1), the proposed approach is evaluated without considering harvested energy. In the *second scenario* (scenario 2), harvested energy is considered for evaluating MDP algorithm. The maximum harvested energy per node is taken as 200 Joules. Total number of sensor nodes are varied from 25 to 200 and simulation results are presented for 200 rounds.

Fig. 4(a) and Fig. 4(b) show the number of rounds in which all the nodes are connected for first scenario and second scenario respectively. It can be seen from Fig. 4(a) and Fig. 4(b) that network remains connected more number of rounds using the proposed MDP algorithm in comparison to the randomized switching algorithm [6]. In randomized algorithm [6], the sustainability condition (in terms of survival of a node) for future time slots has not been considered. At each iteration of randomized switching algorithm only one node with highest load is selected for balancing. In proposed MDP based algorithm, all the nodes which are not having sustainable energy are selected for switching. Switching decision is chosen by MDP algorithm based on residual energy of the node. Further, it can be seen from Fig. 4(a) and Fig. 4(b) that as number of nodes increases, the height of the tree also increases. Moreover, the nodes near to the sink are overloaded with heavy traffic and their energy deplete quickly. Hence, the number of rounds, in which the network is connected, is reduced sharply as number of nodes increase.

Fig. 5(a) and Fig. 5(b) show the rounds at which the first node (in the network) deplete all its energy for first scenario and second scenario, respectively. It is shown that the first node (in the network) depletes its energy early for randomized algorithm in comparison to the proposed MDP algorithm. With harvested energy the proposed MDP algorithm gives significant sustainability to the network in comparison to randomized switching algorithm. This is an important result because disconnection of a node in a tree based sensor network leads to network partitioning.

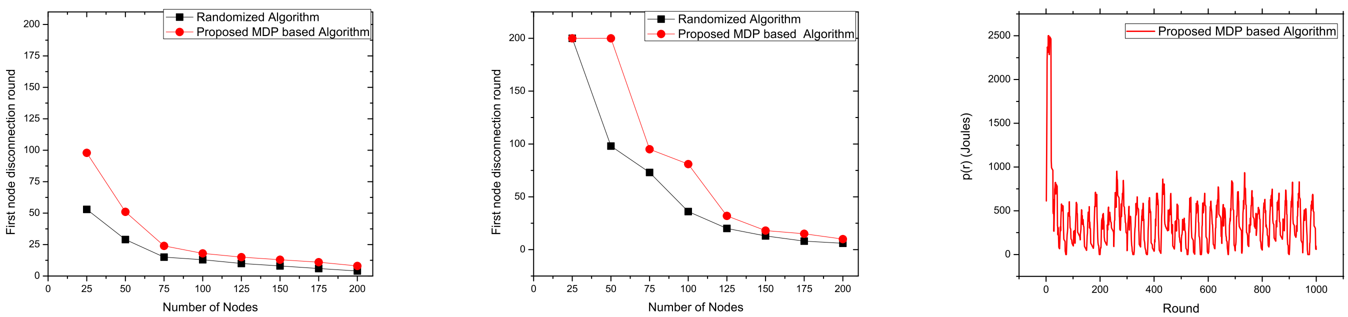
Simulation study has been performed (as shown in Fig. 3(c)) to evaluate the performance of protocol under various weather conditions such as sunny, cloudy and rainy. If the day is sunny, the nodes harvest more energy and the network is alive for more number of rounds as compared to cloudy and rainy days. As the number of nodes increase, the connectivity status of the network reduces due to more load on the nodes which are placed near to sink.

Fig. 4(c) and Fig. 5(c) show the performance of proposed protocol in terms of path energy balancing parameter $p(r)$ as defined in section III-A. Simulation results are presented for 200 rounds and 1000 rounds in Fig. 4(c) and Fig. 5(c), respectively. Number of sensor nodes is considered as 400. It can be observed from Fig. 4(c) that path energy balancing parameter is high in initial rounds and the tree is imbalanced. The proposed MDP algorithm is not invoked in initial rounds because all nodes are having sustainable energy. Energy hungry nodes (without sustainable energy) invoke the proposed



(a) (b) (c)

Fig. 4: Number of data collection rounds network is connected for (a) scenario 1 (b) scenario 2 (c) Difference of maximum and minimum path energy for scenario 2 for 200 rounds



(a) (b) (c)

Fig. 5: First node disconnection data collection round for (a) scenario 1 (b) scenario 2 (c) Difference of maximum and minimum path energy for scenario 2 for 1000 rounds

algorithm for energy balancing in the data collection tree. The data collection tree is fully balanced $(p(r) = 0)$ at 73^{rd} round as shown in Fig. 4(c). Further, it can be seen in Fig. 4(c) that $p(r)$ value fluctuates from 0 to 600 (approximately) Joules. Further, similar fluctuations in $p(r)$ value are observed from Fig. 5(c). The fluctuations in $p(r)$ value is due to the variations in node's harvesting energy.

VI. Conclusions and Future Works

A *Markov Decision Process* based algorithm has been proposed in a rechargeable sensor network. The proposed algorithm maximizes the sustainable time of data collection trees in terms of data collection rounds. Further, a switching decision is taken on the basis of residual energy of the node to balance the tree. From the simulation results, it has been observed that the network is connected for more number of data collection rounds in comparison to an existing randomized switching approach. Further, it has been observed that the node sustainability time is improved significantly using the proposed method. Energy utilization has been studied by varying various weather conditions. Network connection statistics have been studied in the presence and absence of harvesting energy. As a future research challenge, MDP-based switching can also be applied in other types of network architectures, such as, clustered network and wireless sensor-actor network. Further, the authors would like to investigate the performance of the protocol in a real-field sensor network.

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