Active Energy Management for Harvesting Enabled Wireless Sensor Networks

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***Abstract*—In this work, we propose a novel control based scheme for energy management in wireless sensor networks with energy harvesting capability. The problem is viewed as a queue control problem where the objective is to maintain a reference energy level of the energy storage device. A validated nonlinear queueing model is considered and a robust nonlinear controller is considered whose convergence properties are established analytically. The proposed control algorithm incorporates predictions of the energy to be harvested which are generated using the recently proposed Accurate Solar Irradiance Prediction Model (ASIM). The combined control and prediction scheme is evaluated using analysis and simulations. Preliminary simulation results conducted on the NS-3 simulator demonstrate the ability of the scheme to achieve its design objective as the energy level oscillates about values close to the desired level.**

***Index Terms*—Wireless sensor networks, Energy harvesting, Energy management, Non-linear Control**

I. Introduction

Wireless Sensor Networks (WSNs) constitute a well established paradigm of wireless on demand systems, serving a number of applications such as patient monitoring, weather forecasting, surveillance, military, wild life monitoring and agriculture [1]. The fixed battery design approach, adopted at their early stages of development, poses significant size and lifetime challenges. Recent developments in energy harvesting technologies and their integration in WSNs, can significantly contribute in alleviating these challenges leading to more effective designs [2].

The harvesting energy capability penetrates in all layers of network protocol design and a number of harvesting aware protocols have been proposed in literature [3]. It is well established that such energy harvesting aware protocols, can be greatly improved upon availability of energy prediction strategies, which generate solar irradiance predictions to be used for better energy provisioning. A number of energy prediction schemes have been proposed in literature [4], [5]. Such prediction schemes can lead to better energy management of the available and harvested resources and lead to protocols with improved properties. A number of energy management schemes and protocols which take into account the harvested energy and prediction policy have been proposed in literature [3], [6], [7], [8]. The problem often takes the form of energy efficient transmission and in a number of cases this has been cast in a queueing theory framework. In [9] the problem is posed as a utility maximization problem subject to energy constraints, in [10] transmission policies are proposed which maximize the average long term importance of the reported data, in [11] activation times are determined so that the number of interesting events is maximized and finally in [12] the maximization of the long term averaging sensing under energy constraints is considered.

In this paper, we represent the rechargeable battery at each node as queue accommodating energy "packets", and unlike previous work we view the energy management problem as a queue control problem where the control objective is to regulate the dissipated energy (by controlling the transmission rate) such that the battery level converges to a desired level. We use a validated nonlinear model of the queueing dynamics [13] and consider a robust nonlinear controller which also takes into account energy predictions. The stability properties of the algorithm are established analytically. The performance of the proposed scheme is also evaluated using NS-3 simulations. Actual solar irradiance data in Austria, obtained from [14] is used to generate the predictions and update the battery level. Energy predictions are obtained using our recently proposed ASIM scheme [5]. Our results indicate that the proposed scheme is able to converge to energy level values which are close to the desired level. The significance of this work lies on the demonstrated effectiveness of adopting the queue control based techniques, developed for congestion control, for energy management in WSNs. This paves the way for the development of a wide class of such energy management schemes.

The paper is organized as follows. In section II we formulate the energy management problem. We present the proposed control algorithm and establish its convergence properties. In section III we evaluate its performance using NS-3 simulations and finally in section IV we offer our conclusions and future research directions.

II. Control Based Energy Management

We view the energy management problem in WSNs as a queue control problem. The battery is modeled as a queue

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where energy packets are stored. The amount of energy stored in the network is denoted by $x(t)$. Unlike traditional WSNs, in harvesting enabled sensor networks, the battery can receive energy with a particular rate denoted by E_{in}. Since energy is utilized for particular network functions, energy stored in the battery is lost with a rate which is denoted by E_{out}. It has been pointed out in literature [15], [16] that energy arrivals and departures from the battery can be modeled as Poisson processes with means E_{in} and E_{out} respectively. We thus consider the battery as an M/M/1 queue. It has also been shown in [13] that, based on the steady state properties of the queue, the following nonlinear model can be used to model the queueing dynamics.

$$\dot{x}(t) = \begin{cases} max(-E_{out}(t)\frac{x(t)}{1+x(t)} + E_{in}(t), 0) & x = 0 \\ -E_{out}(t)\frac{x(t)}{1+x(t)} + E_{in}(t) & 0 < x < x_{max} \\ min(-E_{out}(t)\frac{x(t)}{1+x(t)} + E_{in}(t), 0), & x = x_{max} \end{cases} \tag{1}$$

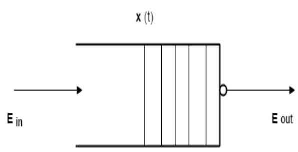


Fig. 1: Energy Storage in battery as M/M/1 queue

We adopt, this model for our energy management design and analysis. The rate E_{out} with which energy is removed from the battery and is made available for network functions, is the control variable, as this can be adjusted. Our control objective is to regulate E_{out}, so that the energy stored in the battery has a fixed value x_{ref} . Keeping a fixed value x_{ref} , ensures that the battery is not depleted and that some energy is always stored for crucial and emergency operations. Another important attribute is that the rate with which energy enters the battery $E_{in}(t)$, can be predicted using the ASIM model. We denote this prediction as $\hat{E}_{in}$. We incorporate the prediction in the nonlinear controller proposed in [13] to consider the following control law:

$$E_{out}(t) = max[\rho(t)\frac{1+x(t)}{x(t)}[\alpha\tilde{x} + \hat{E}_{in}], 0] \tag{2}$$

where $\tilde{x}(t) = x(t) - x_{ref}$ is the queue error, $\dot{\tilde{x}}(t) = \dot{x}(t)$ and α is a design parameter and $\rho(t)$ is introduced to provide robustness against $x(t)$ attaining small values close to zero and is given by.

$$\rho(t) = \begin{cases} 0 & \text{if } x(t) \leq 0.01, \\ 1.01x(t) - 0.01 & \text{if } 0.01 < x(t) \leq 1, \\ 1 & \text{if } x(t) > 1. \end{cases} \tag{3}$$

The above equation can be used to update the rate with which energy is made available for network operations. The update will be done every time T which is a design parameter. We assume that the whole amount of energy which is made available to the wireless sensor node is used to send sensed data. So, the more energy is made available to the wireless node, the more data can be sent, and thus more performance is achieved. The rate of the energy made available to the sensor node E_{out} , which is dictated every time step by the control law (2), thus determines the rate with which sensed data is sent every time step.

A. Stability Analysis

Theorem 1: The control law described by equation (2) guarantees that $x(t)$ is bounded and converges close to x_{ref} with time, with an error that depends on the upper bound of the estimation error ϵ.

Proof:

Consider the Lyapunov function:

$$V(x) = \frac{1}{2}\tilde{x}^2 \tag{4}$$

Differentiating with respect to time, we get

$$\dot{V}(x) = \tilde{x}\dot{\tilde{x}} \tag{5}$$

Our objective is to show that $\dot{V}(x) \leq 0$ outside a specific neighbourhood of the equilibrium point x_{ref}. Equation (1) dictates 3 different cases to be considered based on the value of x.

Case 1: $(0 < x < x_{max})$

when $(0 < x < x_{max})$ two subcases can be further identified.

Case 1.1: $E_{out} > 0$

Substituting $E_{out}(t)$ from equation (2) in (1) yields:

$$\dot{x}(t) = -\rho(t)[\alpha\tilde{x} + \hat{E}_{in}] + E_{in}(t) \tag{6}$$

Further substituting equation (6) in (5) yields:

$$\dot{V}(x) = \tilde{x}\dot{\tilde{x}} = -\alpha\tilde{x}^2\rho(t) - \rho(t)\tilde{x}\hat{E}_{in} + E_{in}\tilde{x} \tag{7}$$

Equation (1) dictates 3 additional subcases which depend on the value of x.

Case 1.1.1: $(x(t) > 1)$

when $x(t) > 1$ then according to equation (3), $\rho(t) = 1$. Substituting the latter in equation (7) yields:

$$\dot{V}(x) = -\alpha\tilde{x}^2 - \tilde{x}\hat{E}_{in} + E_{in}\tilde{x} \tag{8}$$

Let the estimation error be denoted by λ such that:

$$(E_{in} - \hat{E}_{in}) = \lambda \tag{9}$$

We assume that the error is upper bounded by a constant ϵ such that:

$$|\lambda| < \epsilon \tag{10}$$

Substituting equation (9) in equation (8) yields:

$$\dot{V}(x) = -\alpha\tilde{x}^2 + \lambda\tilde{x} \tag{11}$$

Completing the square

$$\dot{V}(x) = -(\sqrt{\alpha}\tilde{x} - \frac{\lambda}{2\sqrt{\alpha}})^2 + \frac{\lambda^2}{4\alpha} \tag{12}$$

It follows that for

$$|\tilde{x}| \geq \frac{\epsilon}{\alpha} \tag{13}$$

$$\dot{V}(x) \leq 0 \tag{14}$$

The right side of equation (12) is not negative definite because near the equilibrium point x_{ref} i.e for the region $|\tilde{x}| < \frac{\lambda}{\alpha}$, the positive term $\frac{\lambda^2}{4\alpha}$ dominates the negative quadratic term $-(\sqrt{\alpha}\tilde{x} - \frac{\lambda}{2\sqrt{\alpha}})^2$. However, $\dot{V}$ is negative outside the neighbourhood ($|\tilde{x}| < \frac{\lambda}{\alpha}$), for the region $|\tilde{x}| \geq \frac{\lambda}{\alpha}$ as shown by equation (14). With ϵ being the boundary of the neighbourhood, any solution starting in the neighbourhood will remain therein for all the future times since $\dot{V} \leq 0$ for the region $|\tilde{x}| \geq \frac{\lambda}{\alpha}$. Hence, solutions are uniformly bounded [17]. Further $V(x)$ is monotonically decreasing until the solution enters the neighbourhood. Therefore, we can conclude that the solution is uniformly ultimately bounded [17]. Moreover, the boundary can be made arbitrarily small by adjusting the value of the design parameter α.

Case 1.1.2: $(x(t) < 0.01)$
when $x(t) < 0.01$, according to the equation (3) the value of $\rho(t) = 0$. Substituting $\rho(t) = 0$ in equation (6):

$$\dot{x}(t) = E_{in}(t) \tag{15}$$

Substituting the latter in equation (5) yields:

$$\dot{V} = E_{in}\tilde{x} \tag{16}$$

Since $x < x_{ref}$, it follows that $\tilde{x} < 0$ and since in addition E_{in} is always positive it follows that $\dot{V} \leq 0$.

Case 1.1.3: $(0.01 \leq x(t) \leq 1)$
when $0.01 \leq x(t) \leq 1$ then according to equation (3), $\rho(t) = 1.01x(t) - 0.01$. Substituting $\rho(t)$ in equation (7) yields:

$$\dot{V} = -\rho[\alpha\tilde{x}^2 + \tilde{x}E_{in}] + E_{in}\tilde{x}(t) \tag{17}$$

Since $x < x_{ref}$ it follows that $\tilde{x} < 0$ which in turn results in $\dot{V} < 0$.

Case 1.2: $E_{out} = 0$
According to equation (1).

$$\dot{x}(t) = E_{in}(t) \tag{18}$$

Two subcases can be further identified.

Case 1.2.1: $E_{in}(t) = 0$
Substituting $E_{in}(t) = 0$ in equation (18), $\dot{\tilde{x}}(t) = 0$ and $\dot{V}(x) = 0$.

Case 1.2.2: $E_{in}(t) > 0$ Since $E_{in}(t) > 0$, It follows that after some time $t_2 \geq t_1$ we will have $\tilde{x}(t) \geq 0$ for $t > t_2$ and $\tilde{x}(t)$ will be growing with time t. Increasing $\tilde{x}(t)$ implies increasing $x(t)$ which means that there exists a time t_3 close to the t_2 i.e $t_3 \geq t_2 \geq t_1$ such that $E_{out}(t)$ takes the value:

$$E_{out}(t) = \rho\frac{1 + x(t)}{x(t)}[\alpha\tilde{x} + \hat{E}_{in}] \tag{19}$$

Since $\tilde{x} < 0$, and $\dot{x} = \dot{\tilde{x}}(t) = E_{in} \geq 0$, it follows that $\dot{V}(x) \leq 0$.

Case 2: $(x = 0)$
When $x = 0$, then according to equation (2), $E_{out} = 0$ and substituting the latter in equation (1) yields:

$$\dot{\tilde{x}}(t) = max[E_{in}(t), 0] \tag{20}$$

Equation (20) dictates 2 additional subcases.

Case 2.1: $E_{in}(t) = 0$
when $E_{in}(t) = 0$, then $\dot{\tilde{x}}(t) = 0$ and $\dot{V}(x) = 0$.

Case 2.2: $E_{in}(t) > 0$ Since $E_{in}(t) > 0$, it follows that after some time $t_2 \geq t_1$ we will have $\tilde{x}(t) \geq 0$ for $t > t_2$ and $\tilde{x}(t)$ will be growing with time t. Increasing $\tilde{x}(t)$ implies increasing $x(t)$ which means that there exists a time t_3 close to t_2 i.e $t_3 \geq t_2 \geq t_1$ such that $E_{out}(t)$ takes the value:

$$E_{out}(t) = \rho\frac{1 + x(t)}{x(t)}[\alpha\tilde{x} + \hat{E}_{in}] \tag{21}$$

Since $\tilde{x} < 0$,

$$\dot{x} = \dot{\tilde{x}}(t) = E_{in} \geq 0 \tag{22}$$

leading to $\dot{V}(x) \leq 0$.

Case 3: $(x = x_{max})$
When $x = x_{max}$, considering $x_{max} > 1$, according to equation (3), $\rho = 1$ Substituting $\rho = 1$ in equation (7) results in:

$$\dot{V}(x) = -\alpha\tilde{x}^2 + \lambda\tilde{x} \tag{23}$$

Completing the square:

$$\dot{V}(x) = -(\sqrt{\alpha}\tilde{x} - \frac{\lambda}{2\sqrt{\alpha}})^2 + \frac{\lambda^2}{4\alpha} \tag{24}$$

Thus for $|\tilde{x}| \geq \frac{\epsilon}{\alpha}$, it follows that $\dot{V}(x) \leq 0$.

III. Performance Evaluation

In this section, we evaluate the performance of the proposed approach using simulations conducted on the Network Simulator (NS-3). We considered a network of 100 harvesting enabled wireless sensor nodes that were placed in an area of $1500 \times 1500\, m^2$ using a uniform random distribution. 802.11 transceivers were used with the transmission power set to $7.5\, dBm$. The commonly used Friss loss propagation model was adopted. A randomly selected set of 20 source/sink pairs initiate the communication in the network by transmitting packets at a rate of $2.048\, kbit/s$ each where, each packet is restricted to a size of $64\, bytes$. The packets were relayed between nodes based on the OLSR (Optimized Link State Routing) protocol. All measurements were obtained after $100\, sec$ which provides sufficient time for the OLSR algorithm to converge to its equilibrium state. The harvesting enabled nodes periodically update the energy harvesting status and decide on the rate with which data will be transmitted based on the discrete time version of equation (2). The control period is denoted by T and is set in the reference scenario equal to $T = 30\, sec$. The harvested energy which is used to update the energy level in the battery, is derived from real data solar irradiance sets obtained in Austria [14]. Each dataset contains solar irradiance for two years (2011 and 2012) having the granularity of one value per 30 minutes. The data was also used to generate energy predictions according to our recently proposed ASIM scheme [5]. We have run multiple simulation runs to establish that the energy consumption for packet transmission is of $0.0025\, J/packet$. We assume that the battery capacity is $1\, J$. The parameter α which affects the convergence properties of the algorithm was set to 1. Two desired energy levels x_{ref} were considered: $0.3\, J$ (120 packets) and $0.5\, J$. We also assume that each node is persistent in the sense that it always has data to send.

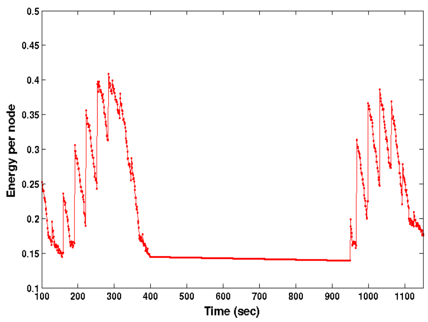


Fig. 2: Energy Storage when x_{ref}=0.3 J

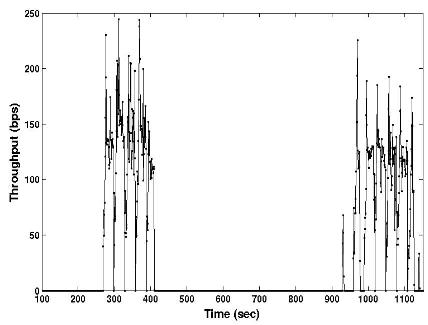
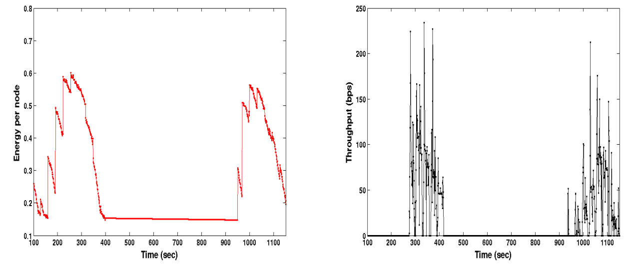


Fig. 3: Throughput when x_{ref}=0.3 J

In Fig. 2, 3 we show the results obtained for the case of $0.3\,J$ reference value. In Fig. 2 we show the battery level recorded for one of the nodes whereas in Fig. 3 we show the total throughput achieved. Our results indicate that at time periods where the energy input is positive the energy management policy is able to regulate transmission such that the battery level converges to values which are close to the reference value which is $0.3\,J$. In addition, during the same periods consistent high throughput is reported. Moreover, when there is limited energy input due to low availability of harvested energy, the battery level drops to the minimum permissible value and the throughput drops to zero. In Fig. 4, we show the corresponding plots for the case of the reference value being equal to $0.5\,J$. Similar behavior is observed.

IV. Conclusion and Future work

In this work, we view the energy management problem as a queue control problem and propose a nonlinear control strategy which incorporates predictions. The convergence properties of the algorithm are established analytically and the effectiveness of the proposed approach is demonstrated through simulations conducted on the NS-3 simulator. The reported simulation results are preliminary and the robustness of the scheme with respect to changing parameters such as the period T and α will be investigated. The significance of this work lies on the demonstrated effectiveness of adopting the queue control based techniques, developed for congestion control, for energy management in WSNs.



(a) Energy Level (b) Throughput

Fig. 4: Energy level and Throughput when x_{ref}=0.5 J

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