ADABCAST: ADAptive BroadCAST Approach for Solar Energy Harvesting Wireless Sensor Networks

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***Abstract*—The problem of message broadcasting from the base station (BS) to sensor nodes (SNs) in solar energy harvesting wireless sensor networks (EHWSN) is considered in this paper. The aim is to ensure fast and reliable broadcasting without interfering with upstream communications (from SNs to BS), whilst taking into account energy harvesting constraints. An adaptive approach is proposed where the BS first selects the broadcast time slots, given a wake-up schedule for the SNs (the time slots where the SN are active and in receiving mode). Hence, the SNs adapt their schedules. This is then iterated seeking optimal selection of the broadcast time slots, so as to minimize broadcast overhead (transmitted messages) and latency. Our approach enables fast broadcast and eliminates the need for adding protocol overhead (redundancy), compared to the existing solutions. Hidden Markov Model (HMM) and Baum-Welch learning algorithm are used for this purpose. Numerical results confirm that our scheme performs the broadcast operation in less time, and by reducing the broadcast overhead, as compared to state-of-the-art approaches.**

I. INTRODUCTION

Energy Harvesting(EH) from the environment emerges as the appropriate solution to enable large scale deployment of sustainable wireless sensor networks in the future. However, satisfying communication requirements in the presence of an erratic (ambient) energy inflow is a nontrivial problem that depends on network protocol / traffic dynamics and on the adopted EH technology. Existing protocols and architectures should be revisited and rebuilt upon an energy model that exploits this new feature, while faithfully reflecting the real world constraints for harvesting [1]. To this end, several models and policies relying on energy prediction models have been introduced for EH enabled wireless communication systems. Among them, in this paper we focus on message broadcasting, which is a key service in ubiquitous wireless communication networks. We consider local broadcasting (one-hop) over downstream links, i.e., from the base station (BS) to the sensor nodes (SNs), in solar Energy Harvesting Wireless Sensor Networks (EHWSN). The aim is to provide fast and reliable broadcast without interfering with upstream communications, whilst taking into account EH constraints. Existing solution for WSN such as [2] do not apply in the new environment EHWSN, as they do not consider EH constraints.

In this paper, an efficient local broadcast policy is developed that emphasizes the importance of selecting the optimal time slots for broadcast. In particular, these time slots should coincide as much as possible with those in which SNs are active with the radio in listening mode (wake-up periods), as this facilitates the correct and prompt reception of broadcast messages. Instead of adding redundant messages to increase reliability, which has been explored in [1], the proposed solution minimizes the number of time slots for broadcast in an attempt to reduce the broadcast count (number of transmissions required to ensure correct delivery) at the BS and allow SNs to preserve their energy. Hidden Markov Models (HMM) [3] and the Baum-Welch learning algorithm [4][5] are used for this purpose. The main idea is to estimate the network model and its dynamics to predict the most suitable time slots for broadcasting. After that, the SN parameters are modified (control action) to change their behavioral patterns, so as to increase the likelihood that the nodes will pick at least one of the identified time slots. Estimation and control are cycled in a loop to allow adaptation to changing conditions in the energy processes. Note that broadcasting slots in our framework cannot be assigned deterministically as they depend on the stochastic energy arrival process. We analyze the proposed solution and compare it against the algorithm of [1], that to the best of our knowledge is the only work from the literature considering broadcasting in EH environments. Our results confirm that the proposed algorithm improves energy efficiency and reduces the broadcast latency.

The remainder of this paper is organized as follows. Section II lists the related work. Section III presents the assumptions, the network and energy models. The proposed solution is described in details in Section IV. Section V evaluates ADABCAST by simulations and mathematical analysis and compares it to [1]. Finally, Section VI draws the conclusion.

II. RELATED WORK

1) Physical Layer Models and Policies: Existing EH physical layer models consider power allocation and channel conditions such as fading. Yang et al. [6] tackled the transmission completion time minimization problem in a single-user additive white Gaussian noise channel for EH wireless communication systems. They proposed to adaptively change the transmission rate according to the traffic load and available energy in order to minimize the transmission completion time. Another policy, proposed in [7], introduces a finite storage rechargeable battery and seeks to minimize the time delivery of data packets to their respective destinations, assuming an M-user AWGN (Additive White Gaussian Noise) broadcast channel. The transmission policy is subject to the causality of energy arrivals, as well as to the finite battery capacity and energy overflows. Besides the finite energy capacity, QoS of wireless links in EH environments has been considered in [8], where a finite state Markov chain has been exploited to model the communication channel. The solution derives the effective capacity for the power allocation policies and relies on the fact that the more stringent is the effective capacity, the faster is the decay of the transmission rate. However, the main drawback of theses solutions is that they do not consider the energy consumption at the receivers.

2) Channel Access Models and Policies: Ensuring perpetual operation of SNs in the presence of EH constraints rises the challenge of designing new communication protocols that control the source of energy consumption at node level. As the radio is the main source of energy consumption, channel access protocols play a central role in controlling wireless communications and the radio by managing the harvested and consumed energy in a way that guarantees sustainable operations. An analytical approach for the design of a wireless node has been proposed in [9], where the authors studied the performance of an EH node using a Markov model that takes into account EH, event arrival processes, and the queuing of events. The authors of [10] proposed an EH based cooperative communication policy that adopts cooperative relay selection to improve the performance of EH communication systems. This is achieved using the available information on channel conditions and energy. Kuan et al. [1] developed a new solution for broadcasting under EH constraints. It applies erasure coding to guarantee the transmission reliability for EH wireless devices. Throughput and the probability of receiving broadcast messages are maximized by configuring the broadcast period and the erasure coding parameters. To our knowledge, this is the only work that considers broadcasting in EH environments.

III. Assumptions and Models

A. Assumptions

The proposed solution addresses the problem of broadcasting in asynchronous and homogenous EHWSN. Time is slotted and each slot time suffices for the transmission of a full broadcast message. Time slots are also grouped into broadcast frames (W slots per frame) and our algorithm seeks to reliably transmit exactly one broadcast message to all the sensor nodes within each time frame. We suppose that a single broadcast message is constructed at the BS in the beginning of every time frame. Note that this may entail the transmission of the same broadcast message over multiple time slots as only a subset of the nodes is generally awake in any time slot. We assume that the BS is powered by the energy grid or a power source which is considered unconstrained, while the sensor nodes are equipped with solar EH capability and are located within the communication range of the BS, forming a start topology (assumed). Every SN has a small capacity of energy storage that ensures the activities during one time slot, say E_{max}. SNs apply a contention based Medium Access Channel (MAC) protocol such as [11], [12] to access the shared communication channel. The BS is assumed to have full knowledge about the radio duty cycle and the energy arrivals for each SN. This knowledge is periodically updated through upstream messages from the nodes to the BS. We also assume that SNs are *time synchronized* with each other and with the BS. Although time synchronisation is challenging in WSN, effective implementations in real platforms of high precision protocols have demonstrated in the literature [13], protocols such as such as [14], [15] maybe used for this purpose.

B. Energy Model

To enable tracking the energy level at the SNs, a proper energy model is needed that accurately captures the dynamic behavior of the EHWSN in terms of power consumption and generation (through solar energy harvesting in our case). The effective energy at node level is determined as the difference between these two contributions. The reception of broadcasted messages from the BS represents the main source of power consumption, besides nodes's regular activities such as the communication of the sensed data to the BS.

Referring to the central limit theorem[16], [17], the distribution of the sample means tends toward the normal distribution as the sample size increases regardless of the distribution from which we are sampling. The effective energy in turn (as the difference of two Gaussian RNs) follows a Gaussian distribution with expectation $(E_H - E_c)$ and standard derivation $(\sigma_H + \sigma_C)$. We then suppose the two continuous random variables (RNs) that represent respectively the energy arrivals and energy consumption to follow Gaussian distributions with expectations and (E_H, E_c) and standard deviations (σ_H, σ_C). Note that the every SN is modelled with two RVs, each having a separate expectation and standard deviation, although they are assumed to follow the same distribution (Gaussian). Energy neutral operation (ENO) is achieved iff $E_{max} \geq E_{\text{eff}}(t) \geq 0$ with $t = 1, \ldots, W$, where W denotes the number of slots in a frame. Consequently, a given SN can receive a broadcast message in any slot t iff $E_{\text{h}}(t) \geq E_{\text{c}}(t)$.

C. Network Model and Solution Overview

Each SN can be in two states, namely, ON ("1") and OFF ("0"). In the former, the node is awake with the radio turned on (receiving mode), whereas in the latter the node is either sleeping or busy with other activities (e.g., sensing, transmission, etc.). The BS cannot track the status of all nodes in each time slot. However, the SNs periodically send to the BS some parameters that allow capturing their ON / OFF (temporal) behavior through a Hidden Markov Model (HMM). So, an HMM is maintained for each SN and is used to assess, at the BS, the most suitable time slots for broadcasting. This is done through a *training* phase that is executed by the BS as follow. ON / OFF sequences are generated at the BS for all the SNs and for a high enough number of frames. Hence, an optimal set selection algorithm is applied to these sequences to retrieve the time slots in the frame that assure maximum coverage of the SNs, i.e., we seek the transmission schedule (which will be fixed across time frames) that allows reaching the highest number of SNs, while entailing the minimum number of time slots. This is achieved using the generated ON / OFF sequences, which are treated as prototype behaviors of the nodes. After having located the access slots, the BS executes the Baum-Welch algorithm for all the HMMs. This allows adjusting the HMM model parameters in an attempt to increase the probability that each SN will be in state ON in at least one of the picked access slots, in each frame. Note that some of the HMM parameters are not under the direct control of the BS (especially those related to the energy arrival). However, others can be controlled (i.e., those related to the protocol behavior) and the idea is to adjust these to ensure that all the SNs will be ON in at least one of the identified access slots with high probability. To summarize, the BS first learns the behavior of the nodes, from which it decides the most suitable access slots for broadcast (broadcast schedule) and then adapts some of the protocol parameters at the SN side to increase the effectiveness of the identified broadcast schedule. The broadcast count is defined as the number of BS transmissions (time slots) required to deliver a broadcast message in a single frame (i.e., to reach all the SNs if possible, or at least the maximum number thereof). The proposed solution has the advantage of increasing the likelihood of reaching all the SNs with the minimum number of broadcast count, and thus with the minimum latency. Another advantage is that the selection of the optimal set of time slots allows the SNs to release the remaining time slot for other scheduled activities and services, such as data gathering and the communication of the sensed data to the BS.

IV. Solution Description

The proposed model has two phases. *i)* the BS level, and *ii)* the SN level. The steps of each phase are described in the following.

A. BS Level

The proposed solution is centralized, as the BS maintains a HMM for every SN, through which it computes and distributes the broadcast schedule. The BS level algorithm runs in three phases. i) The first phase entails the generation of observation sequences from the current HMMs. ii) The second phase consists in applying an optimal set selection algorithm on these sequences, which returns the broadcast time slots (broadcast schedule). Finally, iii) in the third phase the Baum-Welch learning algorithm is used to adjust the HMM parameters associated with each SN, so as to increase the likelihood that the SNs will be ON in at least one of the time slots identified in phase 2). The BS communicates the new HMM model parameters to the SNs, which will be used at the nodes to (statistically) determine their ON/OFF behavior. This process can be executed at network setup time, and the obtained scheduling can be used for a long period of time until a significant change takes place, such as a change in the statistics governing the energy arrival process or the sensing behavior leading to either a high number of missed nodes or a high broadcast count, which demand an update of the training process and the re-execution of the three phases of the algorithm.

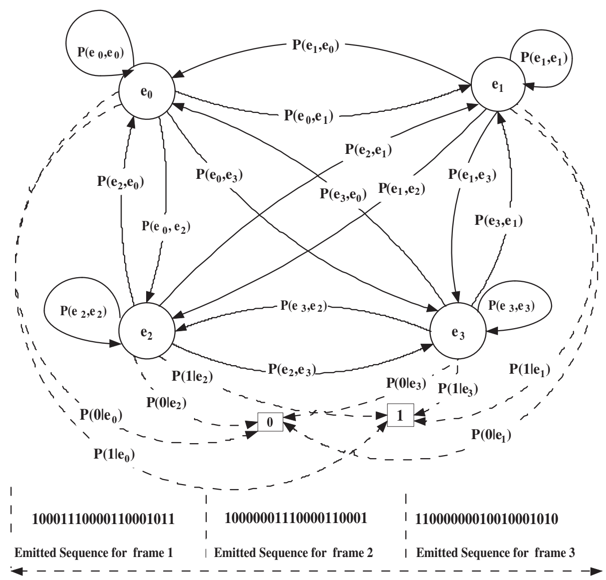

Fig. 1. Proposed HMM

HMM: for each SN, an HMM is defined by the tuple $M =< \mathcal{S}, \mathcal{A}, \boldsymbol{T}, \boldsymbol{E} >$, where $\mathcal{S}$ is the set of hidden states, $\mathcal{A}$ is the set of alphabet symbols or observations, $\boldsymbol{T}$ is the transition probability matrix for hidden states and $\boldsymbol{E}$ is the emission probability matrix, containing the probabilities that a certain hidden state $i \in \mathcal{S}$ generates observation $j \in \mathcal{A}$.

The model considers the availability of energy at node for receiving the broadcast message, as well as its readiness. The latter depends on the node activity. For $\mathcal{S}$, we have that the HMM at any time slot, t, can be in one the following states:

- e_0: Representing a low energy level and a high probability that the node is busy.
- e_1: Representing low energy and a low probability that the node is busy (high probability of readiness).
- e_2: High energy and a high probability of the node is busy and
- e_3: High energy and low probability the node is busy.

Set $\mathcal{A}$ contains the possible observations that in the considered broadcast model are, $\mathcal{A} = \{0, 1\}$, where any of the two symbols is generated depending on the available energy at the node. "0" and "1" refer to OFF and ON, respectively.

$\boldsymbol{T}$ is the transition probability matrix governing the transitions among hidden states. The transition probability from state i to state j, with $i, j \in \mathcal{S}$, is denoted by $T(i,j) = P(X_t = j | X_{t-1} = i)$. If N is the cardinality of $\mathcal{S}$, we have $\sum_{j=1}^{N} T(i,j) = 1, \forall\, i \in \mathcal{S}$.

In our model the transition probabilities are the product of two independents RVs. The first one represents the energy arrival times which is modeled using a Gaussian distribution with expectation p. The second RV concerns the readiness of the node to receive the broadcast message during the time slot, which depends on the node's activity. Let us assume that a node is busy in a time slot with probability q. It is then ready to receive a broadcast message with probability $1-q$. This yields the following transition probabilities:

$$P_{e_0e_0} = P_{e_2e_0} = P_{e_1e_0} = P_{e_3e_0} = q(1-p), \tag{1}$$

$$P_{e_1e_1} = P_{e_2e_1} = P_{e_0e_1} = P_{e_3e_1} = (1-q)(1-p), \tag{2}$$

$$P_{e_2e_2} = P_{e_3e_2} = P_{e_1e_2} = P_{e_0e_2} = qp, \tag{3}$$

$$P_{e_3e_3} = P_{e_2e_3} = P_{e_0e_3} = P_{e_1e_3} = p(1-q). \tag{4}$$

- **E**: The matrix of emission probabilities of the symbols in **A** by the HMM hidden states. The probability that the state "i" generates the observation "j", say, $P(O_t = j|X_t = i)$, is denoted $E(i,j)$. The matrix **E** has to satisfy the constraint:

$$\sum_{j=1}^{M} E(i, O_j) = 1 \forall i \in S. \tag{5}$$

1) Phase 1: the BS first trains the HMM of every node. The observation sequences generated by the HMM follow a discrete distribution where the emission probabilities change depending on the current hidden state. Theses sequences are composed of "1" and "0" values, which correspondingly mean "ON" and "0" the SN's radio "OFF", in the corresponding time slot, as presented in Fig. 1. The radio behavior of each SN is determined by the emitted sequences for each time slot within the frame duration. The decision on whether the node will turn ON or OFF the radio during the next time slot depends on the probability of generating "0" or "1", i.e., based on the proposed energy model presented in Section III-B and the node readiness to receive a broadcast messages. The effective energy is formulated during each time slot within the frame based on the energy harvesting and the energy consumption. When a node has an effective energy beyond a given threshold, say β, it is put in a state of high energy (e_2 or e_3 depending on its availability), and in the remaind states otherwise. Recall that in the proposed energy model, the random variables corresponding to the energy harvested and the energy consumed follow a Gaussian distributions with expectations, E_H, E_c, respectively, and standard deviations σ_H and σ_C, respectively.

2) Phase II: After training the HMM model for several frames, the BS applies the set selection algorithm that explores the intersections between nodes schedules (all time slots of the frame) that match "1" value, in every time-frame. The algorithm allows retrieving the set of frames providing a minimum number of time slots intersection that assures nodes coverage (or the maximum of intersections). This leads to a minimum broadcast count and releases the remaining unselected time slots for other activities such as communicating the sensed data to the BS. We define the most likely sequence by the matrix of frames selected by the algorithm.

Parameter	**Value**
q	0
$P(0\|e_0), P(0\|e_1), P(0\|e_2), P(1\|e_3)$	1
$P(1\|e_0), P(1\|e_1), P(1\|e_2), P(0\|e_3)$	0
E_h expectation (mj)	20
E_c expectation (mj)	40
Energy Threshold β (mj)	250
Initial effective energy (mj)	0
DATA Packet Size (Byte)	32
Time_Slot length (ms)	5
Number of iterations	10

TABLE I
SIMULATION PARAMETERS.

3) Phase III: Once the most likely sequences in hand, the third phase allows to execute the Baum-Welch algorithm for each node, with the desired generated frame as input. The algorithm belongs to a family of algorithms called Expectation Maximization (EM) algorithms [18]. It allows to obtain a derived HMM model that maximizes the probabilities of reproducing the most likely sequence. In our case the most likely sequence is expressed by maximizing the product of all the new HMM models ($\hat{\gamma}_1$,$\hat{\gamma}_2$,...,$\hat{\gamma}_n$) for d each node as follow:

$$\begin{cases} Argmax_\gamma & (\prod_{i=0}^{i=n-1} P(O_i|\gamma_i)) \\ i = 0, 1, ..., N & \gamma_i =< S_i, A_i, \Pi_i, T_i, E_i > \end{cases} \tag{6}$$

The result is a set of updated HMM models obtained after adjustment of the initial HMM model parameters (transition and emission probabilities). Finally the BS communicates the parameters of the derived HMM models to theirs corresponding nodes.

B. Node Level

As aforementioned, at the end of the third phase of the BS, each node receives the derived HMM. Since we cannot adjust the parameters related to energy harvesting that are strongly dependant on the stochastic nature of the weather conditions and its impact on the amounts of energy arrivals, the key idea is to adjust the power of the node units responsible for energy consumption. These parameters should be set in a way that allows to meet the probabilities of the derived HMM model proposed by the Baum-Welch learning algorithm. The power consumption units that may be adapted are the receiving unit (e.g. adapting the duty cycle and radio wake up periods), the microcontroller and the sensing unit (e.g., adapting sensing sampling periods).

V. SIMULATION STUDY

In this section, the proposed solution is compared to [1]. For the latter, the source (K) and redundant data message (N) are set respectively to ($K = 2$), ($N = 3$). Table I summaries the experiments simulation parameters. At the beginning of simulation, we suppose that there is no activity, i.e., the initial value of q is set to 0.

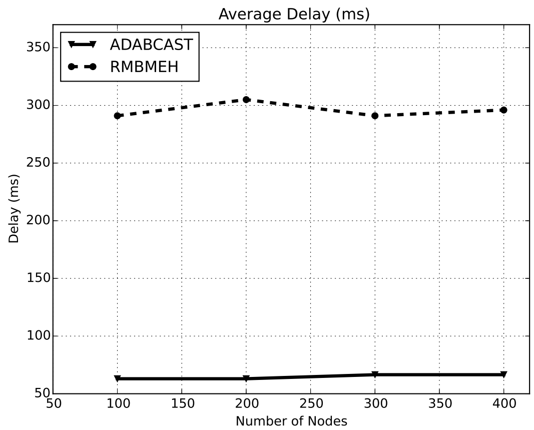

Fig. 2. Average delay vs. numbr of nodes

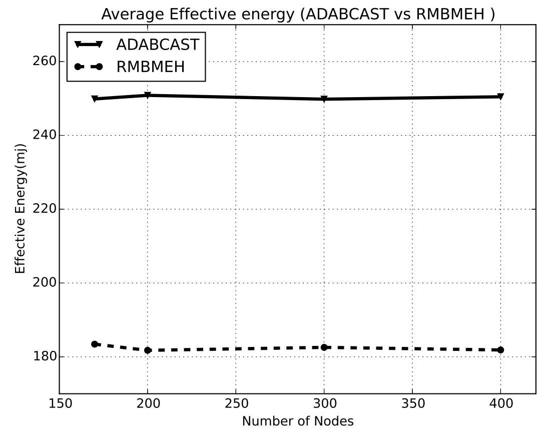

Fig. 4. Average effective energy vs. number of nodes

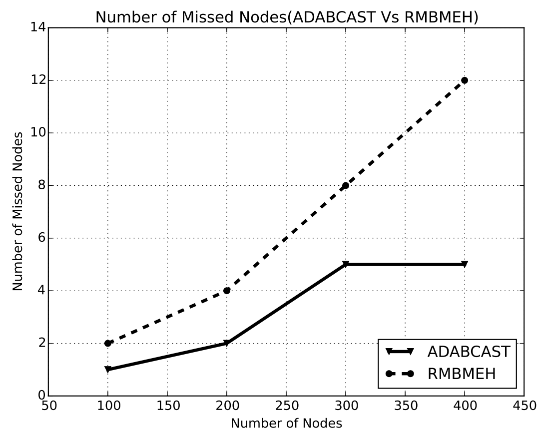

Fig. 3. Number of missed nodes vs. number of nodes

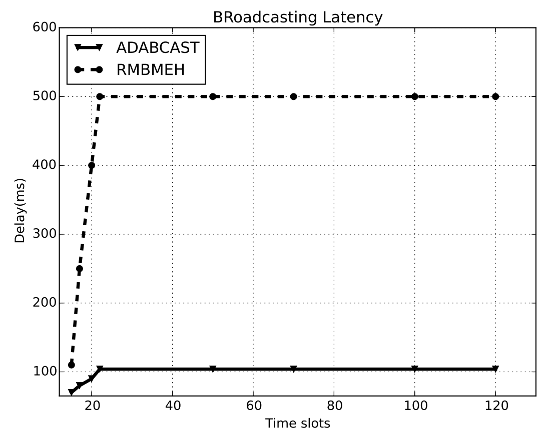

Fig. 5. Average delay vs. numbr of nodes

We first exam the performance of the solution in terms of the average effective energy in the network vs. the number of nodes. The frame size has been fixed to 20 in this step, while varying the number of nodes from 100 to 400. Fig. 2 shows that the proposed solution clearly out-performs RMBMEH with respect to the broadcast delay. ADABCAST has delays around 65 while RMBMEH has values around 300, i.e. more than 75% reduction. This is because in the proposed solution the BS broadcasts at a certain selected time slots, contrary to RMBMEH that uses a broadcast over the whole frame with erasure coding. Fig.3 plots the number of missed nodes, i.e., number of nodes that do not receive the broadcast message. Superiority of ADABCAST is also obtained, but more importantly, the figure shows that the difference between the two solutions increases with the number of nodes. This is due to the use of coordinated slot in ADABCAST, contrary to RMBMEH that uses erasure coding, which is considerably influenced by the increase in the number of nodes. Fig.4 shows that the effective energy of the proposed solution (ADABCAST) exceeds that of (RMBMEH) by almost 30% This can be explained by the fact that the nodes in ADABCAST do not receive redundant messages, which causes less energy consumption. To investigate the impact of the frame size, the number of node have been set to 100 while varying frame size. Fig. 5 shows the broadcast delay. Both solutions have an increasing delay at the beginning then a convergence. However, the convergence of ADABCAST is much faster (after 22 slots vs. 100), as well as the converged value of the delay ($104ms$ vs. $500ms$). The growth of this metric for both solutions is explained by the following. For lower frame sizes, messages are not received by all nodes, and from the frame size 22 in ADABCAST (res. 100 in RMBMEH), messages are received by all nodes, which explained the convergence. It is trivial that the increase in the frame size increases the likelihood to reach a larger number of nodes (less missed nodes). Fig. 6 shows that the number of missed nodes in the proposed solution is much lower than RMBMEH and converges very rapidly, i.e., after 22 slots all the nodes receive the message (none is missed), while

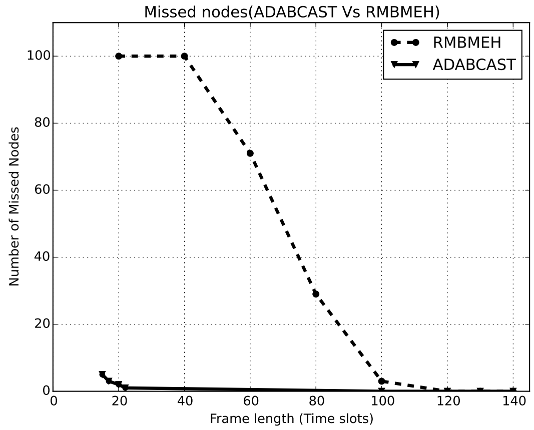

Fig. 6. Missed nodes vs. frame size

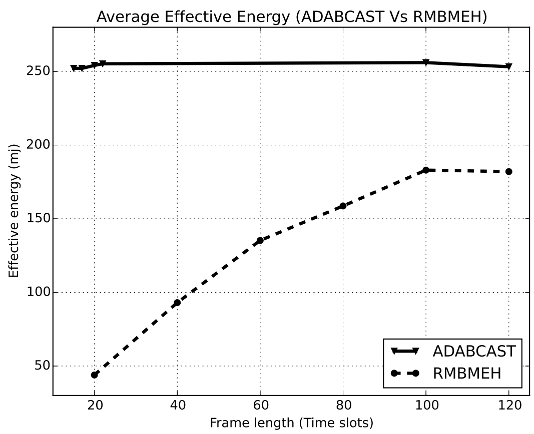

Fig. 7. Average effective energy vs. frame size

RMBMEH needs more than 100 slots for this convergence. This increase also allows to give more time for harvesting, thus to have more effective energy, which explains the growth of both plots in Fig. 7. Faster convergence of ADABCAST is also obtained for this metric.

VI. Conclusion

In this paper, the problem of message broadcasting from the base station (BS) to sensor nodes (SNs) has been considered in solar energy harvesting enabled wireless sensor networks. To tackle this problem, we proposed a solution based on normal distribution for both energy harvesting arrivals and energy consumption for each SN during regular time intervals within a frame. A greedy policy for calculating the optimal set of time slots for performing broadcast operation has been proposed. the policy is based on a Hidden Markov Model coupled with the Baum-Welch Estimation Maximization algorithm. The proposed solution has been compared by simulation to [1], the only related solution that treats the same problem in energy harvesting environment. The results demonstrated a significant performance increase in terms of total average effective energy in the network, broadcast count, and latency. A simple scenario where a single broadcast message per time frame has been considered. As a perspective, we plan to generalize the model for handling any number of messages. This will require the update of the policy and the use of some queuing theory techniques to manage the messages.

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