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A low complexity online controller using fuzzy logic in energy harvesting WSNs

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Abstract In this paper, we present a fuzzy logic based scheme for a two hop energy harvesting (EH) wireless sensor network (WSN). Incorporating data and energy causality constraints, discrete transmission rates, finite energy and data buffers, a fuzzy model is developed which uses network throughput, battery level and channel gain as inputs. The fuzzy scheme is then compared with optimum, modified optimum, and Markov decision process (MDP) schemes in terms of computational complexity, throughput, battery level and data buffer capacity. The throughput results show that the fuzzy online scheme preforms closely to the compared schemes and avoids battery depletion even when the number of discrete transmission rates are increased.

Keywords wireless sensor networks, energy harvesting, cooperative communications, fuzzy logic

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1 Introduction

An energy harvesting (EH) equipped wireless sensor node has the potential to create self-sustainable wireless sensor networks (WSNs) [1]. Barring physical calamity, these EH nodes have the potential to autonomously run forever [2], with little to no maintenance. However, the harvested energy is usually quite modest and intermittent in nature as it depends on readily available ambient EH sources [3]. Therefore, the throughput performance of such WSNs hinges upon the efficient usage of the harvested energy and requires a scheme catering for practical constraints such as limited battery capacity, a maximum energy that can be harvested, limited data buffer size, and a set of allowable transmission rates. In addition, this scheme must not be too computationally intensive, since the devices are necessarily limited in processing power, and it should be easily implementable in small, low power, battery operated, EH embedded systems such as [4].

The rapid deployment of these devices at a large scale, such as Internet of things (IoT), necessitates the use of multi-node cooperative networks [5]. Cooperative communication using EH relay nodes has been shown to be effective in extending the range and overcoming slow channels and physical obstacles [6]. These relay nodes can transmit the data to multiple destinations and multiple hops can be used to create a large, distributed network. This cooperative behavior will cause an increase in the energy consumption

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and has to be managed in a manner that maximizes throughput while maintaining the availability of the EH nodes. In [7], for a single relay cooperative network, the authors investigated the optimal partial relaying strategy that maximizes the source stable throughput for a given relay throughput. However, the analysis is valid for Poisson data and Bernoulli energy arrivals. In [8], an optimal algorithm for energy allocation which maximizes throughput for an EH node with a finite battery capacity has been developed. However, it is an offline method which requires a non-causal knowledge of incoming energy and assumes the data rates available for transmission to be continuous. In [9], harvest-then-cooperate protocol is proposed in which both the source and relay nodes initially harvest energy from an access point (AP) in the downlink mode and cooperation between source and AP is done in the uplink.

The two main methods of relaying, amplify and forward (AF), and decode and forward (DF) are used with different protocols in [10]. Multiple nodes are considered in [11] for both direct and cooperative transfer of data with energy salvage under the ideal assumptions of infinite battery and no constraint on transmission power. The need for a simple and efficient power allocation scheme using Markov decision process (MDP) is identified in [12] and both offline and online cases are discussed. The approach is computationally expensive and a low-complexity heuristic method is derived based on the MDP, which assumes an infinite data buffer and works best with an exact knowledge of the variables involved. Reinforcement learning based MDP model for energy management was proposed in [13] with focus on harvesting from indoor light and outdoor wind. Transmission-time-optimization and throughput energy-efficiency are considered as event-trigger based robust-optimal control problems in [14]. Transmission policy is based on significant changes in the battery and data queue length. While energy and data arrivals are considered unknown, no limits are placed on the battery and transmission rates. In [15], delay analysis is performed on EH-WSNs to show that frequent updates cost a considerable amount of energy and a trade-off exists that must be taken into account by the controller. Two further schemes are discussed in [16] with a similar scenario of a control center supplying power. Convex optimization and water filling methods have been used in [17] to derive optimum transmission policies for one and two parallel relays.

Any scheme for a relay in an EH-WSN will have to cater for many practical constraints mentioned above. Online schemes are more desirable, but their complexity must be low for efficient implementation in small, low power, battery operated, EH embedded systems. In this paper, we therefore offer a low complexity solution by using a fuzzy logic strategy while achieving almost similar performance to existing optimal and computationally expensive schemes (e.g., [8]). The intuitive design of the fuzzy logic avoids the use of complicated algorithms and can run efficiently on modern hardware [18]. Fuzzy logic has been successfully applied in [19] for optimized routing in WSNs, however, it only focuses on routing decisions and not on throughput. A simple fuzzy model for energy management is presented in [20] without considering the effect of channel and rate selection. Recently, fuzzy logic is applied in [21] to determine the throughput performance of an opportunistic relay in a half-duplex cooperative EH-WSN with similar relay buffer and packet size. Significant gains are observed in performance parameters and the results shown to have approached an offline scheme. Motivated by this work, in this paper we apply fuzzy logic for a conventional cooperative network with EH capable full duplex nodes with variable packet sizes. To the best of our knowledge, fuzzy logic has not been used in such a scenario.

Specifically, the contributions are summarized as follows.

- A fuzzy logic controller is proposed that takes into account energy and data causality while incorporating the practical constraints of limited battery size, random energy arrivals, and discrete transmission rates (as defined in the standards).
- The results of fuzzy logic controller are compared with two schemes: an existing optimum method [8] and a simulated finite horizon MDP method. The comparison results are provided in terms of the computational cost, amount of sent data, battery level, and relay buffer size. The optimum method is modified for fair comparison, by including discrete transmission rates.

The system model is described in the following section. Section 3 presents a fuzzy logic controller and describes optimum, modified optimum and simulated MDP methods used for performance comparison. Section 4 presents comparison in terms of performance parameters and computational complexity.

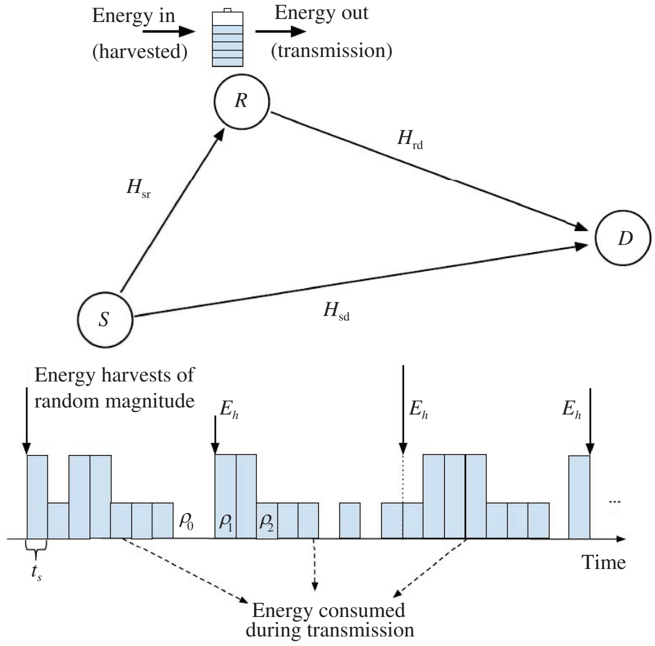

Figure 1 (Color online) Basic cooperative communications model with EH.

2 System model

We consider a two hop cooperative communications network consisting of three wireless sensor nodes: the source $\boldsymbol{S}$, the destination $\boldsymbol{D}$, and an EH capable full duplex relay $\boldsymbol{R}$, as depicted in Figure 1. A dedicated hardware is assumed for a full duplex operation that effectively suppress self-interference [22]. It is assumed that the residual self-interference (which can modelled as an additive process [23]) is negligible compared to AWGN. In addition, it also provides a fair comparison with an optimal scheme [8], which assumes a single link. The source sends data to the destination via relay using "decode and forward". It is assumed that sending directly to the destination is not possible due to distance or physical obstacles [12]. The relay node is assumed to be EH capable with an independent harvesting unit. The harvested energy, denoted by E_h, is accumulated and stored in a battery of maximum capacity $E_{b_{\mathrm{MAX}}}$. After the n-th EH interval, the energy level of the battery E_b is

$$E_b(n) = E_b(n-1) - E_T(n-1) + E_h(n), \tag{1}$$

where, $E_T(n-1)$ is the energy spent on transmission in the previous EH interval. This process is shown in Figure 1. It is assumed that between two consecutive EH intervals, a finite number of transmission time slots exist, denoted by i. The duration of each transmission slot is denoted by t_s, and assumed to be constant. During these transmission slots the data in relay buffer Q may be sent at any subset of the possible discrete rates, ρ_x, for example

$$\rho_{r,x} \in \{0, 250, 500, 1000, 1250\} \text{ kbps}, \quad x \in X = \{0, 1, 2, 3, 4\}. \tag{2}$$

Note that these transmission modes are a feature of the hardware employed. The example values used in this paper aim to highlight this commonly overlooked practical limitation.

We assume an AWGN channel between relay and destination with variance σ_r^2 having a channel gain denoted by H_{rd}. The relay power required $P_{r,x}$ to transmit at a certain rate $\rho_{r,x}$, and channel bandwidth B can be calculated from the Shannon-Hartley theorem,

$$P_{r,x} = \left(2^{(\rho_{r,x}/B)} - 1\right) N_T, \tag{3}$$

where, $N_T = \frac{\sigma_r^2}{H_{\mathrm{rd}}}$. The total energy consumed at relay during transmission between EH events is, therefore, the sum of the energy consumed for all the elapsed time slots and should be less than $E_b(n)$.

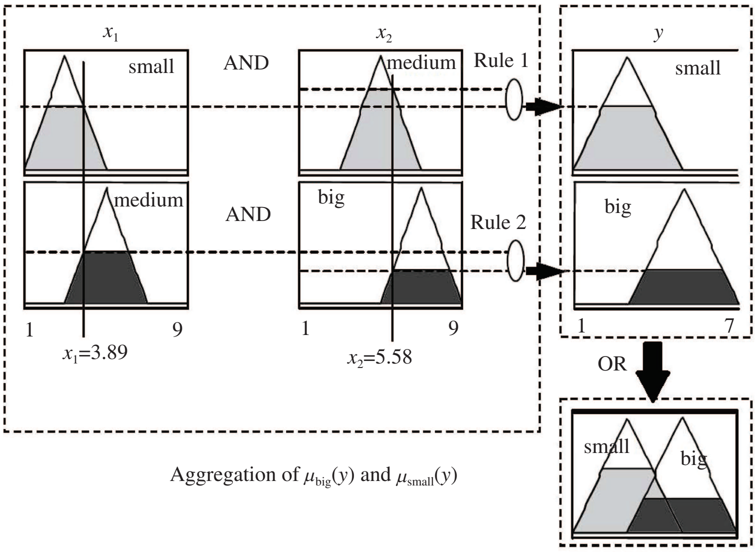

Figure 2 (Color online) Mamdani inference method [25].

For k time slots between harvests, each of constant duration t_s, the transmission energy of the n-th transmission time block can be expressed as

$$E_T(n) = \sum_{i=1}^{k} P_{r,x}(n,i)t_s \leqslant E_b(n). \tag{4}$$

The data buffer Q is filled by source data packets, and emptied when this data is transmitted by the relay to the destination. To avoid Q becoming infinitely large (or overflowing, in practice), the overall average rate of incoming data must be matched by the rate of outgoing data. At any time slot i, after the n-th EH, the size of the data buffer is given by

$$Q(n,i) = Q(n,i-1) + \rho_{s,x}(n,i)t_s - \rho_{r,x}(n,i)t_s. \tag{5}$$

Consequently, the algorithm to determine transmission rate $\rho_{r,x}$ that maximizes throughput at the relay must be designed to achieve a balance between (4) and (5) using (1). In the following, we develop a fuzzy logic controller that aims to achieve the maximum throughput, the trade-off between throughput and data queue size will be a part of future work.

3 Fuzzy logic based EH-WSN

Fuzzy logic is a framework in which logical states have many values in contrast with the binary system of zeroes and ones. This means that it works with values in between absolutely true and absolutely false [24]. The process works by converting an exact value of a variable to a fuzzy truth value. The range of values this variable can take is divided into sub-ranges which corresponds to a fuzzy set (for example ‘high’ or ‘low’) via a membership function. The membership functions convert the value of the input to a fuzzy logic value [25]. Since the membership functions for ‘high’ and ‘low’ may overlap, a single input value can have a certain degree of membership with ‘high’ and a different degree of membership with ‘low’. Conditions on these fuzzy states can be imposed to make fuzzy rules which are used to define the output which each combination of inputs should result in. This is analogous to a truth table of binary logic, but since the fuzzy states can overlap, multiple rules may apply in some degree at the same time. A two input and single output example system is shown in Figure 2 to illustrate how multiple rules may be applied concurrently. The two inputs, (x_1, x_2), are provided as crisp values and each input corresponds to two membership functions. Therefore, x_1 is small and medium, while x_2 is medium and big. This triggers two rules which have an output membership function associated with them. The outputs of the

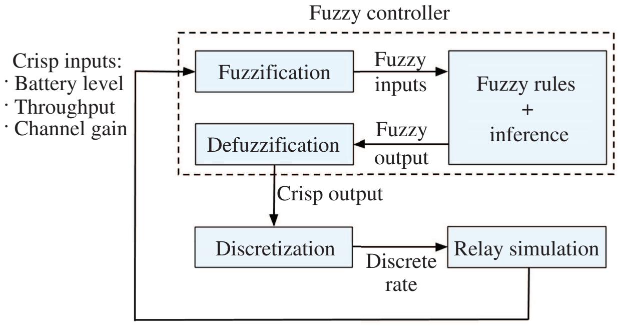

Figure 3 (Color online) Flowchart of fuzzy logic controlled relay.

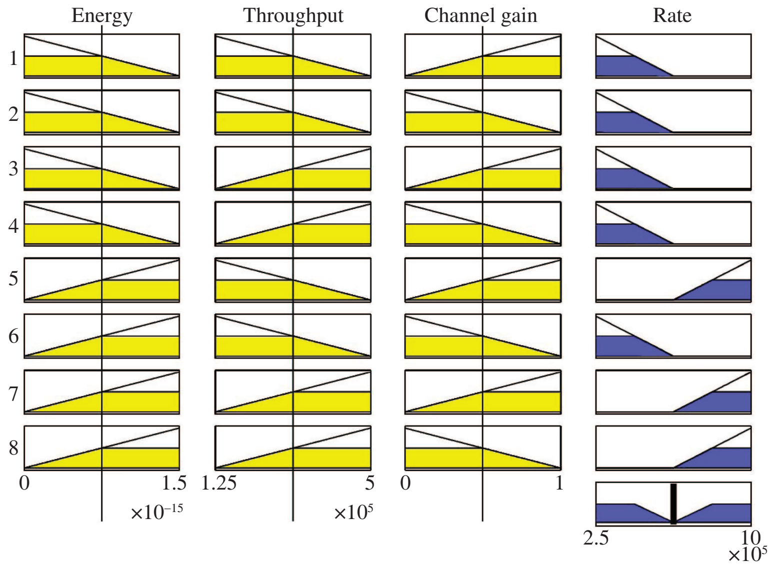

Figure 4 (Color online) Membership functions.

two rules are then aggregated by taking the logical OR, which, in this case, is equivalent to the union of the two results, and gives the final fuzzy membership function for y.

We map this fuzzy logic approach to the system model in Figure 1 and use it to select discrete transmission rates at the relay based on knowledge of current battery level and network throughput during the last transmission interval and channel conditions. It is an online controller that takes into account a finite battery, discrete transmission power levels, fixed transmission slot times and no a priori knowledge of EH. Although other variables such as buffer size $Q(n,i)$, delay, data buffer overflow can be used as input to the fuzzy logic controller, the focus of this paper is to analyze the usefulness of the fuzzy logic in terms of battery level and throughput. The complete fuzzy logic controller used in this paper is shown in Figure 3. The input variables used to determine the rate are the current battery level $E_b(n,i)$, network throughput in the last transmission time slot (average of source and relay throughput), and channel state $H_{\rm rd}$. Each of the three inputs have two triangular membership functions 'high' and 'low'. The output of this controller is the transmission rate and also has two membership functions, 'high' and 'low'. In Figure 4. the first three columns are the input variables, the last column is the output, while each row represents a single rule. The yellow triangles are the fuzzy membership functions which convert the value of the input to a fuzzy logic value. The output column is shown in blue and depicts the membership function for the data rate as output.

Rudimentary logic rules were created, for example, the first row, shows the rule based on low energy $E_b(n,i)$, low previous network throughput, and high gain $H_{\rm rd}$. The output of this rule, in the last column, is 'low' rate. A complete list of the fuzzy rules is shown in Table 1. For a single combination of inputs, some, or all, of the rules may give an output. The union of all of these outputs is taken as the final fuzzy

Table 1 Fuzzy rules for determining transmission rate

Energy	Throughput	Channel gain	Rate
Low	Low	High	Low
Low	Low	Low	Low
Low	High	High	Low
Low	High	Low	Low
High	Low	High	High
High	Low	Low	Low
High	High	High	High
High	High	Low	High

membership function. This fuzzy value is then defuzzified to a crisp value by calculating the centroid of the graph. This procedure is known as Mamdani type fuzzy inference [26]. The fuzzy logic controller was implemented by using the fuzzy logic toolbox in MATLAB.

The output value given by the controller is then quantized to one of the nearest values from the available rates. This rate is then used to simulate data transfer from the relay. The power required for this rate will also be calculated using the other parameters in (3). If the required power is not available, the lower rate is selected which satisfy the battery energy constraint. In order to assess the feasibility, we compare fuzzy controller with two well established schemes, optimum algorithm in [8] and an MDP scheme. These schemes are slightly modified to a full duplex scenario for fair comparison and are explained below.

3.1 Optimum algorithm and modified optimum method

The optimum algorithm in [8] considers continuous data rates, known energy harvests, and data is always available to transmit. These are ideal assumptions and it works by finding a power level and data rate that takes the longest time to either fully charge or discharge the battery. Therefore, the data rates need to be continuous and future EH need to be known. The optimal algorithm was modified to confine its data rates to the subsets of the rates in (2). For example, if the subset of the rates chosen are {0, 250, 1000} kbps, the rate first determined by the optimal algorithm is limited to 0 if the recommended optimum rate was less than 150 kbps, 250 kbps if the optimum was less than 625 kbps, and 1 Mbps if optimum was greater than 625 kbps. The available battery $E_b(n,i)$ level was also considered as a constraint so that the battery would not be accidentally over-depleted while choosing a high transmission rate. Since the optimum rate was not chosen, the new rate is not allowed to be sustained for the length of time recommended by the optimal algorithm.

3.2 Markov decision process controller

The fuzzy logic controller was then compared to an MDP controller. The MDP method finds the appropriate data rate $\rho_{r,x}$ from a set of discrete data rates from (2) by solving Bellman's equation using dynamic programming [27]. A state vector holds all possible combination of states. The state in MDP formulation is 3-tuple (energy levels $E_b(n,i)$, current buffer size of relay $Q(n,i)$, source transmission rate $\rho_{s,x}$). The state probability transition matrix is generated by finding all the possible combinations of state transition and actions. A reward vector assigns a reward value to each state change, in this case reward is proportional to the transmission rate of relay $\rho_{r,x}$. The reward matrix was generated by assigning high rewards for favorable state changes and low rewards for unfavorable ones. If V^* is the maximum achievable reward at state s, then $V^*(s)$ can be found at every state recursively using Bellman's optimality equations

$$V_t^*(s) = \max_a \left\{ R_t(s,a) + \sum_{s'} P_t(s'|s,a) V_{t+1}^*(s') \right\}, \tag{6}$$

where $R_t(s,a)$ is the expected immediate reward when taking an action, a, at time t from the current state s and $P(s'|s,a)$ is the probability that action a in state s at time t will result in state s'.

Table 2 Table of results

Algorithm	Available rate	Average rate	Average buffer	Max buffer	Buffer standard deviation
Optimum	N/A	698.1	N/A	N/A	N/A
Modified I	0, 250, 1000	650.8	N/A	N/A	N/A
Modified II	0, 250, 500, 1000	660	N/A	N/A	N/A
Modified III	0, 250, 1000, 1250	647	N/A	N/A	N/A
Modified IV	0, 250, 500, 1000, 1250	679	N/A	N/A	N/A
MDP I	0, 250, 1000	646.8	58.6	1875	255
MDP II	0, 250, 500, 1000	649.7	31.3	2000	166
MDP III	0, 250, 1000, 1250	647.1	77.6	6100	149
MDP IV	0, 250, 500, 1000, 1250	652.6	56.3	2125	176
Fuzzy I	0, 250, 1000	635.4	79.9	3000	296
Fuzzy II	0, 250, 500, 1000	639.8	35.4	1875	145
Fuzzy III	0, 250, 1000, 1250	649.8	72	5500	122
Fuzzy IV	0, 250, 500, 1000, 1250	653.5	31.8	1875	136

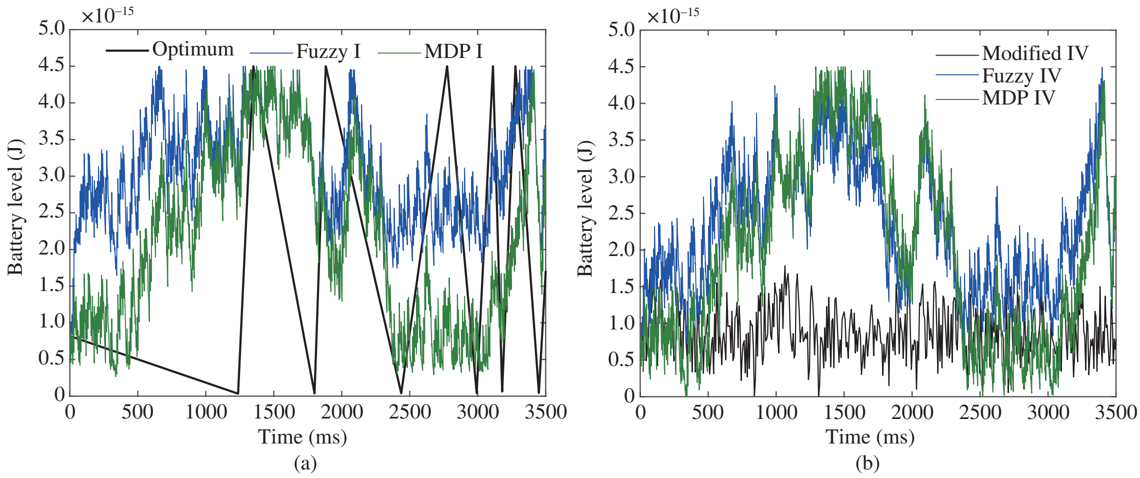

Figure 5 (Color online) Comparison of battery energy level over time. (a) Battery level of optimum, fuzzy I, and MDP I schemes; (b) battery level of modified IV, fuzzy IV, and MDP IV schemes.

4 Simulation results

In this section, we compare the results of fuzzy logic controller with the other two schemes. A consistent set of conditions was used for all the simulations. The maximum capacity of the battery was chosen to be $E_{b_{\mathrm{MAX}}} = 4.5 \times 10^{-15}$ J, the bandwidth $B = 1$ MHz, and the EH level was assumed to be uniformly distributed random variable with an upper bound of 10^{-16} J. The time between the harvests was 15 'time slots', with each time slot representing 0.5 ms. For the fuzzy logic and MDP methods, the source data was modeled as a uniformly distributed discrete random variable with the possible values for the rate being {0, 250, 500, 1000, 1250} kbps. The noise power is assumed to be 10^{-13} W. Initially, the channel gain was kept $H_{\mathrm{rd}} = H_{\mathrm{sr}} = 1$ for a fair comparison (due to the assumption of ideal channels in [8]). The performance in case of Rayleigh fading is discussed in the later half. To summarize, the performance results of different schemes are compiled in Table 2. All the rates are in kbps and all the buffer values are in bits.

Figure 5 shows the battery profile comparison of the three schemes for different sets of data rates. The curves show that rate selection is important in all the schemes as having more available rates results in less chance of battery overflow. Compared to other schemes, fuzzy IV battery level avoids depletion despite the fact that more number of rates are available.

Figure 6 examines the behavior of the data buffer under MDP and fuzzy controller schemes (there is no provision of buffer in optimum scheme). It can be seen from the Table 2 that the average buffer size

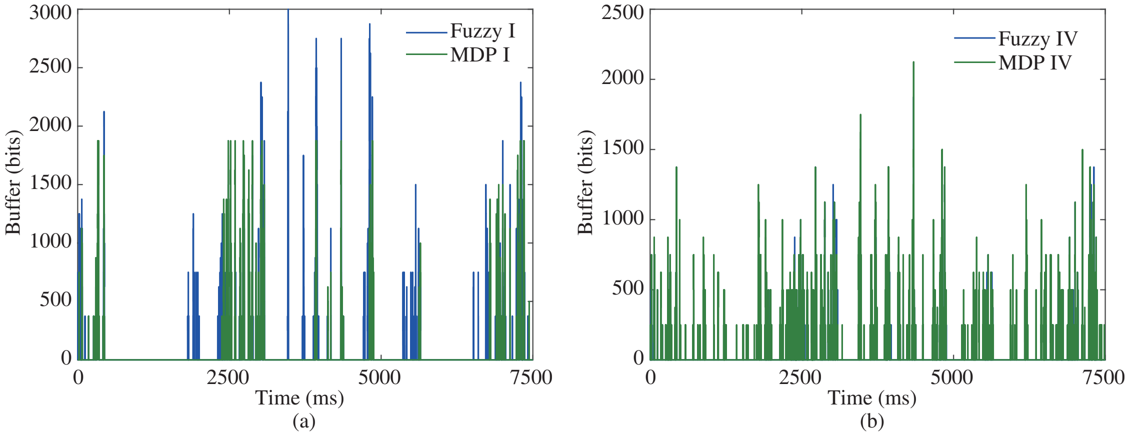

Figure 6 (Color online) Comparisons of buffer size. (a) Buffer size of fuzzy I and MDP I schemes; (b) buffer size of fuzzy IV and MDP IV schemes.

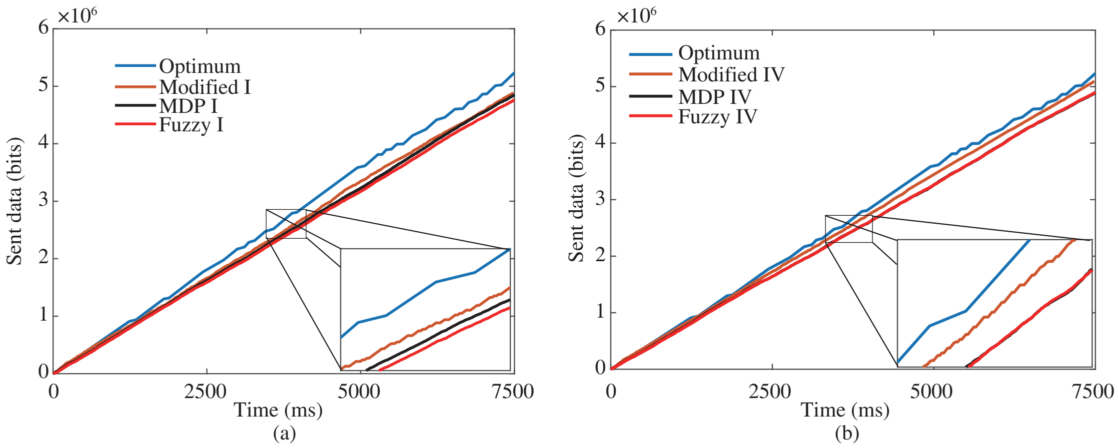

Figure 7 (Color online) Comparisons of sent data over time. (a) Sent data of optimum, modified I, MDP I, and fuzzy I schemes; (b) sent data of optimum, modified IV, MDP IV, and fuzzy IV schemes.

consistently improves in fuzzy controller, except in the case of fuzzy III. In both the fuzzy III and MDP III scenarios, the reason of high average and maximum buffer size is an absence of 500 kbps rate. This absence requires the battery energy to be sufficiently high for 1000/1250 kbps transmission, otherwise a lower rate of 250 kbps is selected. Since in simulations, a uniform distribution of energy profile is used, a lower rate is highly likely and eventually causes lower number of bits to be transmitted and thus increases the buffer size. Comparing the rest of MDP and fuzzy schemes, the table shows a higher improvement in average buffer size of fuzzy controllers. The standard deviation of the buffer size in Table 2 is always lower than the data transmitted in one time slot, which is 625 bits.

A comparison of the data sent by different algorithms over the full range of simulation time has been shown in Figure 7. It can be observed that while the optimum algorithm performs at the maximum possible rate for the given EH, the modified optimum algorithm, the MDP controller, and the fuzzy algorithm all perform in a similar manner. Increasing the available rates also increases the average throughput in all of the methods and fuzzy IV outperforms MDP IV. It is worth mentioning that despite the low computational cost the four fuzzy schemes perform near to the optimum scheme. It must also be noted that out of these methods, only the fuzzy logic and MDP schemes do not have the knowledge of future EH arrivals.

Complexity analysis. The computational complexity of fuzzy logic Mamdani inference method is $O(N_{\rm rule}N_{\rm dim})$, where $N_{\rm rule}$ is the number of fuzzy rules and $N_{\rm dim}$ is the number of dimensions of the input [28]. Since it uses 3 inputs and 8 rules, the complexity is of the order of 24, which remains constant, therefore, the running time of the algorithm for n iterations is $O(n)$. The value iteration of the MDP

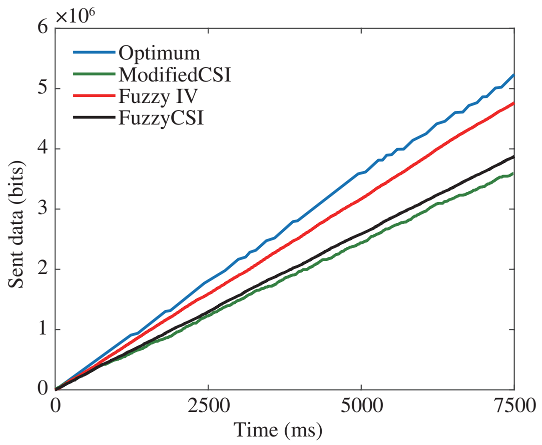

Figure 8 (Color online) Data sent over time with and without channel fading.

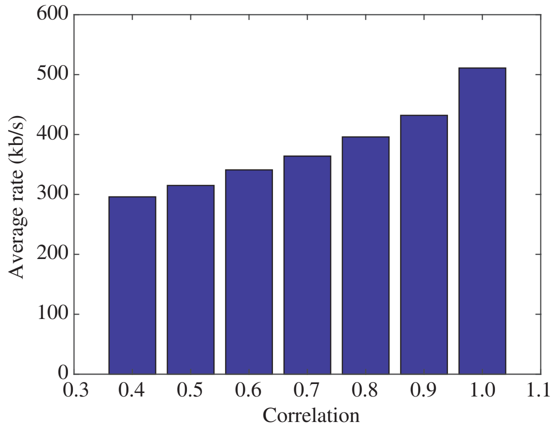

Figure 9 (Color online) Average data rate vs. quality of channel estimate.

controller has computational complexity order of $O(MN^2)$, where M is the action space and N is the state space [29]. In our case there are 5 actions and the states depend on maximum battery divided by the minimum change in battery level, which is 475. This gives the order of calculations to be 1128125, much larger than fuzzy logic. This remains constant, therefore, the running time of the algorithm for n iterations is $O(n)$. The calculations of the optimum algorithm [8], increase as the square of the number of future energy harvests i.e., $O(n^2)$. Therefore, the complexity of the algorithm increases faster than the other two algorithms. It should be noted that the modified optimum algorithm requires even more computations between harvests due to discretization of rates.

Performance analysis with Rayleigh fading. The aforementioned simulations assumed an ideal AWGN channel. In the following, we present results when the channel between the relay and destination is Rayleigh faded. Since the fuzzy logic controller uses channel information to predict the new rate, both the perfect and imperfect channel information scenarios at the relay are considered. In the first scenario, the relay has perfect knowledge of the channel and it adapts the power accordingly to achieve the selected rate. In the second scenario, the relay adapts the power according to the estimated channel $\hat{H}_{\rm rd}$. In literature, a correlation model [30] is often used to define the quality of a channel estimate.

$$\hat{\zeta}_{\rm rd} = \rho\zeta_{\rm rd} + \sqrt{1-\rho^2}\mu, \tag{7}$$

where, $\zeta_{\rm rd}$ ($\hat{\zeta}_{\rm rd}$) is the complex Gaussian distributed random variable whose envelope $H_{\rm rd} = |\zeta_{\rm rd}|^2$ ($\hat{H}_{\rm rd} = |\hat{\zeta}_{\rm rd}|^2$), and ρ is the correlation coefficient between the $\zeta_{\rm rd}$ and $\hat{\zeta}_{\rm rd}$. A higher correlation indicates better estimation.

Figure 8 shows the results of optimum scheme and fuzzy IV in AWGN scenario, and modified optimum and fuzzy IV in Rayleigh fading with perfect channel knowledge. The curves indicate that the fuzzy IV performs better than modified optimum scheme. The average rate of fuzzy IV was noted to be 520 kbps having an increased average buffer level of 375 bits. The average rate against the quality of estimate for fuzzy IV is plotted in Figure 9. The increase in average throughput is obvious with correlation coefficient and it is inline with the mean square error (MSE), $E[(H_{\rm rd}-\hat{H}_{\rm rd})^2]$, between the channel and its estimate. The MSE approximately varies from 31% to 3% as correlation coefficient is increased from 0.4 to 0.9.

5 Conclusion

In this paper, we presented a fuzzy logic scheme to address the throughput problem in EH-WSN. This fuzzy logic model is then compared to an optimum and an MDP scheme. The results show that the on-par performance in terms of computational efficiency, throughput, data buffer length and battery management along with its low computational cost, intuitive implementation, and robust nature, makes fuzzy logic a convenient and powerful tool to handle throughput allocation in EH-WSN. In addition, the simulations indicate that the presence of lower transmission rates is helpful in managing data buffer but higher rates consolidate the throughput. Fine tuning of the rates, membership functions and decision boundaries according to EH, opens avenues for future research.

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