Towards Energy Efficient Adaptive Error Control in Indoor WSN: A Fuzzy Logic based Approach

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Abstract—In populated indoor environments, the radio signal quality is heavily influenced by channel impairments caused by movement of people, obstacles, or radio interferences. In such environments, high packet drop rates lead to frequent retransmissions and increased energy consumption of resource-restricted wireless nodes. To overcome this, we propose a novel Forward Error Correction (FEC) based adaptive error control strategy that employs a cascaded fuzzy inference system to combat communication unreliability. The strategy unifies various heterogeneous metrics such as signal-to-noise ratio, line-of-sight/non-line-of-sight detection and ACK/NACK to closely estimate the low-power links’ quality and based on that, selects an appropriate FEC code to protect packet transmissions. Numerical evaluations are carried out using a realistic indoor fading channel model and IEEE 802.15.4 2.4 GHz modulation format. The performance results obtained from a comparative analysis with static and Adaptive FEC Code Control schemes (AFECCC) conclude that the proposed adaptive scheme guarantees better trade-off (packet error rate and energy-efficiency) for indoor WSN applications.

Keywords—WSN; Forward Error Correction (FEC); Fuzzy; Adaptive FEC; BCH codes

I. INTRODUCTION

Wireless Sensor Network (WSN) technology offers great promise to simplify the installation of a wide range of monitoring and control applications in indoor environments, but practical concerns about unreliable wireless communication between sensor nodes continue hampering its widespread adoption [1, 2]. In a typical obstacles-rich indoor environment, the radio signal is often affected by multipath fading, shadowing etc due to the presence of people and other obstacles; which results in transmission errors and in the worst case, packet transmissions are completely lost.

The Forward Error Correction (FEC) techniques are widely used to reduce transmission errors due to bad channel conditions, but they impose overheads in terms of higher energy consumption due to the transmission of additional (redundant) bits per data packet and increased computational burden of packet en-/de-coding. Therefore, employing a deterministic error control scheme for resource-restricted sensor nodes is not a good choice, especially in indoor spaces where channel error statistics show dynamics on a sub-second granularity. In order to address these issues, we propose an adaptive forward error control strategy that employs a run-time fuzzy inference system to select an appropriate FEC scheme. We use fuzzy logic based approach for number of reasons [3]. First, fuzzy logic control is more robust against imprecise inputs computed by resource-limited sensor nodes. Secondly, fuzzy logic systems do not need a fast processor to make decisions. Thirdly, fuzzy logic needs less data storage for membership functions and rules than conventional lookup tables for nonlinear controllers. To reduce complexity, we propose a novel hierarchical structure of the cascaded fuzzy logic controller that fuses various heterogeneous metrics (signal-to-noise ratio, line-of-sight (LOS)/non-line-of-sight (NLOS) indications and ACK/NACK) to characterize the link quality and to select an appropriate FEC scheme. For evaluation, we use a realistic indoor channel model initially developed for Wi-Fi networks [4]. Comparative evaluations with static FEC schemes and an existing adaptive FEC code control scheme (AFECCC) indicate that our fuzzy logic based scheme offers a better trade-off between packet error rate and energy efficiency as compared to others.

In the next Section, we present the related work. In Section III, our realistic indoor channel model is described, and channel error statistics are verified. In Section IV, the proposed fuzzy logic is detailed with complete details. Section V highlights the performance results using numerical evaluations. Finally, we summarize the work and offer an outlook in Section VI.

II. RELATED WORK

Although, extensive research has been published on using error control techniques in wireless networks, especially in cellular networks, none of these are directly applicable to WSNs. The limited energy and low complexity of the sensor node hardware necessitates an energy-efficient error control strategy to be used. The energy consumption analysis of different error control techniques [5, 6] demonstrates that binary BCH codes (Bose-Chaudhuri-Hocquenghem) are more energy-efficient than Reed-Solomon and convolutional codes. Furthermore, various energy-efficient error control schemes have been discussed for resource-constrained sensor networks [7, 8, 9, 10]. The Authors in [11] discuss an adaptive error control strategy for Bluetooth sensor networks based on the number of hops and quality of the wireless link over Nakagami-m fading channels. In [12], a similar strategy is employed; but these approaches have limitations in terms of uniform deployment of nodes in the monitoring area. But in most of the indoor...
environments, the placement of wireless nodes is rather non-uniform due to structures like doors, walls, and other obstacles. In [13], an AFECCC mechanism is proposed for mobile sensor nodes where packet protection is increased by applying a stronger FEC when receiving transmission errors and strength of error correcting FEC is lowered after successful transmission in a simple multiplicative-increase additive-decrease (MIAD) manner. Its performance depends upon the multiplicative and decay factors which are rather difficult to determine experimentally [14]. In indoor environments, several experiments [2, 16, 17] have been conducted to understand the low-power link dynamics of the IEEE 802.15.4 standard [15]. It is found that low-power links exhibit the dynamics at both, fast time scale (hundreds of milliseconds) and slow time scale (hours) due to multipath fading, shadowing effects of people and other obstacles along with interference from other equipments in the 2.4GHz ISM band. Here, we take such fine-grained link dynamics into account and design an adaptive error control strategy for energy-efficient reliable communication among distributed wireless nodes in stochastic indoor conditions.

III. INDOOR RADIO SIGNAL PROPAGATION AND CHANNEL MODEL

In an indoor environment, various radio propagation modes (reflections, diffractions and scattering) introduce multipath fading of the signal. When there is no LOS signal component, the envelope of the received signal is statistically described by a Rayleigh distribution. If non-fading components (LOS) are dominant, the received signal envelope is Rice distributed [18]. In these fading scenarios, BER performance of the IEEE 802.15.4 2.4GHz physical layer [15] reveals severe degradation in communication quality compared to an AWGN channel (Fig. 1).

To simulate channel conditions close to a real indoor environment [2], we consider an accurate and robust channel model similar to the one proposed for Wi-Fi network [4]. Here, we assume WSN nodes deployment on ceiling, walls or sometimes even on desks in the indoor space. In such a scenario, multipath fading is the combination of a coherent part (represented as Rice distribution) and a diffuse part arising from NLOS components (represented by a combination of Rayleigh and Lognormal Shadowing distributions) (Fig. 2). The time-varying fading process switches between LOS (good) state and NLOS (bad) state depending upon obstacles density. The probability density function is expressed as follows:

\[ P(S) = ARP_{\text{Rice}}(S) + (1 - A) \int_0^{\rho} P_{\text{Rayleigh}} \left( \frac{S}{\sigma_t} \right) P_{\text{NLOS}}(S) dS \quad (1) \]

where

\[ P_{\text{Rice}}(S) = K_b(2\sqrt{S}) \quad (2) \]

\[ P_{\text{Rayleigh}} \left( \frac{S}{\sigma_t} \right) = \frac{1}{\sqrt{2\pi} \sigma_t} \exp \left( -\frac{(10 \log S - N_0)^2}{2\sigma_t^2} \right) \quad (3) \]

\[ P_{\text{NLOS}}(S) = \frac{1}{\sigma_0} \exp \left(-S/\sigma_0 \right) \quad (4) \]

where \( K \) is Rice Factor, \( S \) is received signal power, \( \sigma_t \) is mean received signal power, \( \sigma_0 \) is standard deviation (dB), \( \mu_t \) is mean attenuation (dB). The transition between two states is governed by a first order Markov model with state probabilities \( A \) and \( 1-A \) respectively. Here, \( A \) is called the time-share probability of LOS between transmitter and receiver; defined as follows [4],

\[ A = (1 - \rho)^{-2d} \quad (5) \]

where \( \rho \) is the people and other obstacles density over an occupied area and \( d(m) \) is the length of the ray over propagation area. Furthermore, \( \mu_t \) and \( \sigma_t \) are expressed as \( \mu_t = (3d\rho)^{0.2} \) and \( \sigma_t = \log(55d\rho + 1) + 0.5 \). The path loss and time varying multipath fading is also considered to achieve more realistic signal propagation. Therefore, the total received power \( P_r(d) \) in dB is given by [4],

\[ P_r(d) = P_t - PL(d_0) - 100\log_{10} \left( \frac{d}{d_0} \right) + X_{db} \quad (6) \]

where \( P_t \) is transmission power, \( d \) is transmitter-receiver distance, \( d_0 \) is reference distance, \( PL(d_0) \) is the power decay for a reference distance \( d_0 \), \( \beta \) is the path loss exponent (rate at which signal decays with respect to distance) and \( X_{db} \) is a Gaussian random variable that accounts for time-varying multipath fading and shadowing effects. The Signal-to-Noise ratio \( \gamma \) at the receiver is:

\[ \gamma = P_r(d) - P_n \quad (7) \]

where \( P_n \) is the noise power in dBm. The ratio of bit energy \( E_b \) to the noise spectral density \( N_0 \) is given by:

\[ \frac{E_b}{N_0} = \gamma \quad (8) \]

where \( B(Hz) \) is the receiver bandwidth and \( R_0(\text{bps}) \) is the transmission rate. For IEEE802.15.4 modulation format (DSSS O-QPSK) [15], the bit error probability \( P_b \);

\[ P_b = \left( \frac{E_b}{N_0} \right)^{-\beta} \quad (9) \]

where \( N \) is the number of chips per bit, \( M \) is the number of simultaneously transmitting users. Assuming perfect interleaving at the transceiver, the code word error probability (CEP) for BCH code of length \( n \) with \( t \) error correction capability,

\[ CEP(n, k, t) = \sum_{i=t}^{n} \binom{n}{i} P_b^{i} (1 - P_b)^{n-i} \quad (10) \]

In case if the packet length \( h \) is larger than the code word, then the packet error rate (PER);

\[ PER(h, n, k, t) = 1 - (1 - CEP(n, k, t))^h \quad (11) \]

The procedure [19] is used to obtain appropriate statistics and correlation properties of the fading distributions, assuming parameters \( \beta = 4 \), \( PL(d_0) = 55 \text{dB} \), \( d_0 = 1 \text{m} \), Noise Power \( P_n = -105 \text{dBm} \), node transmission power \( P_t = -10 \text{dB} \), \( R_0 = 250 \text{kbps} \), \( B = 2 \text{MHz} \) [7, 8, 15]. To verify the temporal variation in error statistics generated by channel model, the packet reception rate is computed at different distances. The node transmits 100 packets (each 100 bytes) in one trial, and the same is repeated 10 times at different obstacle densities (0.005, 0.05, 0.15, 0.25) [4]. The recorded PRR at each distance shows a significant variation (Fig. 3) and also confirms the extent of connected, transitional and disconnected regions as a function of distance. These results demonstrate how closely our channel model represents the real world experimental results [2].

IV. FUZZY BASED ADAPTIVE ERROR CONTROL

In the previous section, we have observed that the PRR varies significantly over any distance in the transitional region. In such conditions, the constant use of powerful
FEC reduces the node’s lifetime (quick energy depletion due to more bits transmissions) or the use of simple FEC may not provide sufficient error correction capability in poor channel conditions. Moreover, the adaptive FEC selection as per channel conditions based on either SNR or acknowledgement status (NACK/ACK) is not an appropriate approach either as each metric individually provides only a partial view of the actual link quality. To address this, we propose a cascaded fuzzy logic controller that fuses various heterogeneous metrics with different units and scale (which is non-trivial problem) to better characterize the complex link dynamics and then to select the best FEC code.

A. Cascaded Fuzzy Inference System

To keep the fuzzy inference system manageable with simple fuzzy rules, we designed a hierarchical structure of cascaded fuzzy logic controllers (FLC) and fused multiple metrics into a single decision. At the receiving node, the first FLC estimates channel quality using two metrics (SNR, LOS/NLOS indication) and the decision is sent via a feedback mechanism along with an acknowledgment status to the second FLC (transmitting node) to select an adequate FEC scheme for the next transmission. This approach is generic enough to tune other radio transmission parameters such as back-off, transmission power, data-rate, etc. The complete fuzzy system (Fig. 4) uses Mamdani-type inference and centroid as defuzzification method.

1) Fuzzy Logic Controller for LOS/NLOS Strength Estimation: The primary FLC estimates the strength of LOS/NLOS situation based on two metrics, SNR and LOS/NLOS indication. Although, SNR alone is not able to provide a full characterization of the link status [20], it enhances the accuracy of LOS/NLOS estimation. On the wireless node hardware, a SNR value can be easily determined by subtracting the noise floor from the received signal strength, which can be deduced by sampling the RSSI (Received Signal Strength Indicator) during packet reception and noise floor can be derived from RSSI sample taken just after complete packet reception.

Recently, the chip level analysis has been carried out using IEEE 802.15.4 compliant CC2420 radio to study error patterns in an attenuation and interference environment [21].

We extend the approach to characterize the error patterns in different fading environments. The 802.15.4 transceivers use Direct Sequence Spread Spectrum sequence (DSSS) where a 4-bit symbol is mapped onto a 32-chip PN-code sequence [15].

Fig. 5 shows chip error statistics of 100 byte packet (200 symbols) captured during $10^6$ packets transmissions. In the NLOS situation (Rayleigh/lognormal fading), the Chip Error per PN-code (CEPP) is found to be higher than in the LOS situation, depending upon the LOS component strength in received signal (Rician-fading). Fig. 6 shows the cumulative distribution function (CDF) of CEPP values. The symbols with probability of CEPP greater than 2 i.e. $P(CEPP>2)$ are negligible in a strong LOS situation (Rician factor $K=6$). With very weak LOS component ($K=1$), symbols with $P(CEPP > 2)$ increases (~75%) but remains lower (~21%) for $P(CEPP >= 6)$. In the NLOS situation, symbols with $P(CEPP >= 5)$ are found to be higher (~99%). To generate LOS/NLOS indication, the mean-CEPP value computed over received packet symbols are compared with threshold values. To determine the threshold values, the distribution of mean-CEPP values is examined (Fig. 7). For LOS scenarios (Rician, $K=1, 6$), the Mean-CEPP values remain lower than 4.50. Therefore, a threshold value of mean-CEPP = 4.5 is chosen to provide LOS/NLOS indication based on several numerical evaluations using different packet lengths (results not shown for brevity). The correct detections of LOS/NLOS situation were reported in all cases.

The Membership Functions (MFs) corresponding to linguistic terms of input and output variables are shown in tables I to III. Trapezoidal and triangle MFs are used as they fit the data best. The MFs for SNR are determined on the basis of theoretical BER curve (Fig. 2). For Rician fading (LOS), the BER varies from $10^{-2}$ to $10^{-4}$ when the SNR changes from -3dB to 9dB. The SNR range of 5dB-25dB is required to obtain the same BER range for Rayleigh fading (NLOS). Therefore, the range of SNR for each MF is selected such that the BER range of LOS/NLOS could be distinguished (Table I). For generating LOS/NLOS indication, mean-CEPP value computed over packet length is compared with threshold value. To address the imprecise nature of the information, we introduce a pragmatic approach. A random value in the range $[0.0, 0.6]$ is generated when a node detects LOS situation and similarly, the interval $(0.4, 1.0]$ is used for NLOS situation. Therefore, vague situations are generated when value falls in interval $[0.4, 0.6]$, which represents the instances of imprecise measurements. In total, seven rules are defined to establish the relationship between inputs and output of the first FLC (Table IV).

2) Fuzzy Logic controller for FEC Selection: The second FLC provides the decision about an appropriate FEC to protect packet transmission. It takes into account three inputs:
TABLE I. MEMBERSHIP FUNCTION - SNR (INPUT)

<table>
<thead>
<tr>
<th>Linguistic Value</th>
<th>Function</th>
<th>Values (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Trapezoidal</td>
<td>[-60 -60 -3.5]</td>
</tr>
<tr>
<td>Medium</td>
<td>Triangular</td>
<td>[-3 3 10]</td>
</tr>
<tr>
<td>High</td>
<td>Triangular</td>
<td>[5 17 30]</td>
</tr>
<tr>
<td>V. High</td>
<td>Trapezoidal</td>
<td>[20 30 50 50]</td>
</tr>
</tbody>
</table>

TABLE II. MEMBERSHIP FUNCTION - LOS/NLOS INDICATION (INPUT)

<table>
<thead>
<tr>
<th>Linguistic Value</th>
<th>Function</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS</td>
<td>Trapezoidal</td>
<td>[0 0.4 0.6]</td>
</tr>
<tr>
<td>NLOS</td>
<td>Trapezoidal</td>
<td>[0.4 0.6 1 1]</td>
</tr>
</tbody>
</table>

TABLE III. MEMBERSHIP FUNCTION - LOS/NLOS STRENGTH (OUTPUT)

<table>
<thead>
<tr>
<th>Linguistic Value</th>
<th>Function</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max. LOS</td>
<td>Trapezoidal</td>
<td>[0 0.2 0.3]</td>
</tr>
<tr>
<td>LOS</td>
<td>Triangular</td>
<td>[0.2 0.3 0.5]</td>
</tr>
<tr>
<td>Min. LOS</td>
<td>Triangular</td>
<td>[0.5 0.5 0.7]</td>
</tr>
<tr>
<td>NLOS</td>
<td>Triangular</td>
<td>[0.5 0.7 0.8]</td>
</tr>
<tr>
<td>Max. NLOS</td>
<td>Tripezoidal</td>
<td>[0.7 0.8 1 1]</td>
</tr>
</tbody>
</table>

TABLE IV. RULE BASE FOR LOS/NLOS STRENGTH DETERMINATION

<table>
<thead>
<tr>
<th>Input (1)</th>
<th>Input (2)</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS / NLOS Indication</td>
<td>SNR</td>
<td>LOS/NLOS Strength</td>
</tr>
<tr>
<td>LOS</td>
<td>Low</td>
<td>Min. LOS</td>
</tr>
<tr>
<td>LOS</td>
<td>Medium</td>
<td>LOS</td>
</tr>
<tr>
<td>LOS</td>
<td>High</td>
<td>Max. LOS</td>
</tr>
<tr>
<td>LOS</td>
<td>V. High</td>
<td>Max. LOS</td>
</tr>
<tr>
<td>NLOS</td>
<td>Low</td>
<td>Max. NLOS</td>
</tr>
<tr>
<td>NLOS</td>
<td>Medium</td>
<td>Max. NLOS</td>
</tr>
<tr>
<td>NLOS</td>
<td>High</td>
<td>NLOS</td>
</tr>
</tbody>
</table>

TABLE V. MEMBERSHIP FUNCTION – ACKNOWLEDGEMENT (INPUT)

<table>
<thead>
<tr>
<th>Linguistic Value</th>
<th>Function</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-ACKs</td>
<td>Singleton</td>
<td>[0 1 2]</td>
</tr>
<tr>
<td>2-NACKs</td>
<td>Singleton</td>
<td>[1 2 3]</td>
</tr>
</tbody>
</table>

V. NUMERICAL RESULTS

All experiments are performed in MATLAB using radio and channel parameters (Table VII) corresponding to the IEEE 802.15.4 modulation format [15] and the channel model (Section III) assuming a perfect feedback channel between transmitter and receiver. The radio interference from other devices in the same frequency band is modelled as part of additive noise. To estimate resource consumption of the node, the MATLAB model of the cascaded fuzzy inference system is converted to C-code and compiled using the GCC WinAVR-20100110 compiler with “O1” optimization flag for ATmega128 (4MHz) target platform. The source code occupies 3808 bytes program memory (2.9% of MicaZ FlashROM) and 850 bytes data memory (20.8% of MicaZ RAM). The scheme’s execution consumes 75.78µJ (12630 microcontroller cycles), which is approximately 20% of the energy required to transmit and receive a single bit at \( P_t = -10\text{dBm} \) for a typical MicaZ node.

A. Packet Reception Performance

First, we examine the benefits of our scheme in terms of connectivity at different transmission distances. The time varying channel conditions corresponding to different obstacle densities (0.005, 0.05, 0.15, 0.25) [4] are modeled.
The application of an adaptive error control scheme significantly improves the packet reception rate (PRR) especially over distances, which fall in the transitional region (Fig. 8). Many packets which were lost over larger distances (>15m) during un-coded transmission are now delivered correctly even those larger distances.

Next, we investigate how well our proposed fuzzy logic based adaptation scheme performs against non-linear channel dynamics. We derive time share probabilities for the channel states corresponding to obstacle density (\(\rho\)) = 0.25 [4] and evaluate the PER performance at different communication distances (Fig. 9). With an increase in distance, the un-coded transmissions and low error correcting FEC codes result in higher PER. The online decisions made by the fuzzy inference system ensure reliability at larger distances. Fig 10 shows the percentage of each FEC code selected by the fuzzy system during the same experiment at different distances. At smaller distances, the link quality generally remains good; packet transmissions do not need FEC most of the times. But at larger distances, our fuzzy inference system confirms the opportunistic usage of candidate FEC codes to compete with the performance achieved using stronger FEC code. Similar performance is observed at other obstacle densities (not shown due to space limitation).

B. Energy Efficiency

Energy efficiency is a critical design metric for resource constrained WSN nodes. We define the energy efficiency parameter \(\xi\) as;

\[
\xi = \frac{\min_e R}{e} \quad (12)
\]

where \(e\) is the total energy consumption a packet transmission and \(e_{\min}\) is the energy consumption for an un-coded transmission. The reliability \(R\) is, given by the percentage of transmitted packets being received correctly;

\[
R = \frac{(\chi_{\text{pac}} - \chi_{\text{err}})}{\chi_{\text{pac}}} \quad (13)
\]

where \(\chi_{\text{pac}}\) is the total number of transmitted packets and \(\chi_{\text{err}}\) is the packets received with errors. Independent of any specific hardware, we have adopted a more generic approach by using normalized values [22]. The energy consumed per bit (\(e_b\)) is constant and reception of a bit consumes approx. 75% of the energy required for transmission. Here, the energies consumed in transmission, reception and decoding are taken into account, with negligible encoding energy consumption [5]. Therefore, the minimum energy consumed \(e_{\min}\) for \(\chi_{\text{pac}}\) packets without error control is;

\[
e_{\min} = \chi_{\text{pac}}(n_{\text{bits}} + n_{\text{bits}} \times 0.75) \quad (14)
\]

\(n_{\text{bits}}\) are the total number of bits per packet. The total energy consumed \(e/e_p\) for a packet with FEC is given as;

\[
\frac{e}{e_p} = \chi_{\text{pac}}(n_{\text{bits}} + n_{\text{bits}} \times 0.75 + \frac{e_{\text{dec}}}{e_p}) \quad (15)
\]

where \(n_{\text{bits}}\) represents the total number of bits per packet including the FEC parity bits. The decoding energy \(e_{\text{dec}}\) for a BCH code (\(n, k, t\)) is computed using the number of instructions required by the microprocessor to execute the decoding process [23]. Fig. 11 shows energy efficiency of all schemes at different distances corresponding to an obstacle density of 0.25. The fuzzy based adaptive scheme always shows energy efficiency close to the most energy efficient scheme by selecting lower FECs (\(t=0, 1, 2\)) at lower distances and higher FECs (\(t=5, 7\)) at larger distances.

C. Performance Comparison with AFECCC

In this section, we compare our scheme with Adaptive FEC Code Control (AFECCC), developed for mobile WSN [13]. The AFECCC scheme starts with a drop timer value (DT) that determines the duration for which a particular FEC candidate code is to be used. Depending on received acknowledgement status, DT is updated. The crucial tunable parameters in the algorithm are \(\alpha\), \(T_{\text{max}}\), \(T_{\text{min}}\) and \(\beta\), \(T_{\text{max}}\) and \(T_{\text{min}}\) are channel dependent parameters determined on the basis of Round Trip Time (RTT). The parameters \(\alpha=1\) and \(0<\beta<1\) are used for updating the DT value [13]. For comparisons, we apply same FEC codset (table VII) with parameter settings of AFECCC; \(RTT = 3.936ms\) [14]. \(T_{\text{max}} = 1000ms, T_{\text{min}} = 39.36ms, \alpha = 2, \beta = 0.8\) [13].

The PER trend (Fig. 12) of AFECCC is slightly better than the fuzzy based scheme due to its conservative strategy of staying at higher FEC levels. However, the fuzzy based scheme captures the channel dynamics at a high resolution in time and utilizes FEC candidates opportunistically. To reveal this, we compare the energy efficiency at different obstacle densities keeping communication distance of 10m at which PER performance of both schemes is nearly equal. Fig. 13 shows that the fuzzy based approach becomes more energy-efficient with an increase in obstacle density as compared to AFECCC which makes dominant usage of higher level FEC codes by showing low sensitivity to the temporal variations in channel conditions. To confirm this, we have captured a fine-grain view (Fig. 14) of the adaptation process of both schemes over 800 packets (out of 10,000) at various obstacle density levels [4]. The AFECCC scheme starts using higher order FEC codes at \(\rho \gg 0.10\). This is due to the higher DT value at higher FEC level, which eventually keeps the level constant or reduces it very slowly even after receiving ACKs. On the other hand, fuzzy based approach
employs uniform usage of available FEC codes in the codeset by promptly reacting to link quality variations. From the overall analysis, it is apparent that our fuzzy based adaptive error control offers better trade-off between PER and energy cost as compared to AFECCC.

VI. CONCLUSIONS AND FUTURE OUTLOOK

In this work, we have proposed an adaptive FEC scheme based on cascaded fuzzy inference logic to improve low-power communication reliability in the obstacles-rich indoor environment while keeping resource consumption at a minimum. Using a realistic indoor channel model, an extensive simulation study has been carried out to demonstrate its benefits as compared to static FEC schemes and AFECCC design. Although, the fuzzy based design is evaluated using IEEE 802.15.4 2.4GHz modulation format, it can easily be extended to other low power radio technologies. In future, we plan to conduct real world experiments to evaluate performance of proposed approach. In addition, we will also enhance the channel model by analyzing the effects of time varying obstacle densities for increased realism.

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