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Predictive Protocol Management with Contingency Planning for Wireless Sensor Networks

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***Abstract*— Wireless Sensor Networks (WSN) are a subset of wireless networking applications focused on enabling sensor and actuator connectivity without the use of wires. Energy consumption among the wireless devices participating in these networks is a major constraint on the deployment for a broad range of applications enabled by WSNs. This paper introduces, for the first time, a novel methodology based on predictive protocol management with contingency planning (PPM and CP). This approach allows efficient update of the WSN operational mode in order to optimize the energy utilization based on the time varying characteristics of the Radio-Frequency (RF) in which the network operates.**

I. Introduction

Energy efficiency is a major concern in the deployment of Wireless Sensor Networks (WSN) for industrial, commercial and residential applications. Long-term monitoring in harsh physical environments or near inaccessible locations heightens the need to utilize the sensor nodes' energy resources efficiently since most WSN applications cannot tolerate frequent (if any) battery replacement. The complexity of this problem increases in the context of multi-hop WSNs. In this paper, a novel approach is presented for employing a predictive protocol model with contingency planning (PPM & CP). The premise behind the approach is that providing the WSN nodes with information concerning the operational environment leads to efficiencies in network operation. To illustrate, a collocated and co-channel interference source can cause an excessive number of retransmissions while routing a message from a node within a sensor field to the WSN's base station. The retransmissions expend valuable energy resources and incur additional transmission latency. By efficiently providing the WSN nodes with information concerning the impact the interference can have on its distributed routing protocol, energy efficient routes can be formulated within the network. Therefore, the approach efficiently updates the operational mode of the WSN to minimize energy utilization based on the time varying Radio-Frequency (RF) characteristics in which the network operates.

Figure 1 presents a block diagram of the approach, illustrating both the major functional components and the information flow to accomplish this new methodology. The major functional blocks described are:

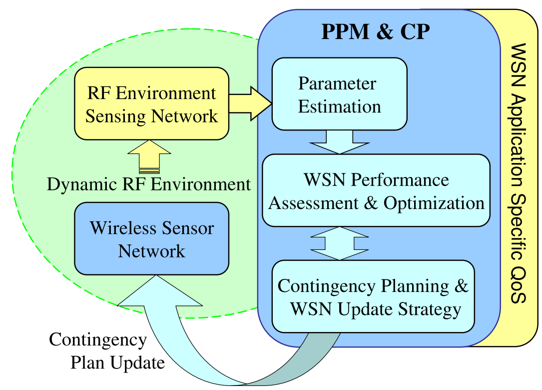

Fig. 1. Block Diagram illustrating PPM with CP.

- WSN
- RF Environment Sensing Network
- PPM & CP

WSN: The WSN is implemented to perform a set of applications which may change over time and which have desired Quality of Service (QoS) requirements e.g. throughput, latency, among others. The WSN is comprised of hardware/software which enables specific capabilities, i.e., operational frequency bands, frequency agility, power control, routing protocols (for multi-hop networks), scheduling algorithms, and so on. In addition, the WSN operates within a dynamic RF environment comprising time varying co-channel interference sources and time varying RF propagation characteristics such as multi-path. Even if the WSN nodes are at fixed locations, dynamics in the environment will significantly impact the RF propagation characteristics, e.g., density of people in a building or changes in the building structure.

RF Environment Sensing Network: The purpose of this functional block is to provide spectrum usage patterns within the operational environment of the WSN. Mangold, et. al. discuss the concept of radio resource measurement for opportunistic spectrum utilization in the context of a homogeneous IEEE 802.11 scenario [1]. Their paper was motivated, in part, by standards activities in the IEEE 802.11k task group [2]. The IEEE 802.11k task group is developing a radio resource measurements extension to the IEEE 802.11 wireless local area network (WLAN) standard. Mechanisms for RF environment sensing are likely to be needed to meet the Federal Communication Commissions (FCC) [3] initiative to use cognitive radios to improve spectrum utilization as well as the Defense Advanced Research Projects Agency (DARPA) Spectrum Agile Radio (SARA) which is part of the Next Generation Communication (XG) Program [4].

Furthermore, the RF environment-sensing network, as proposed in Figure 1, will be used to enhance site specific propagation estimates within the operational environment and capture time varying patterns in the propagation characteristics. It is important to remark that this does not imply measuring instantaneous small-scale multi-path characteristics which are too time sensitive for remote measurement. Instead, measurements would be targeted at capturing large scale changes or patterns in the shadowing characteristics such as building structural changes, population density and variations in inventory. As depicted in the Figure 1, the RF environment-sensing network is separate from the WSN and is not an integrated part of the WSN, as it could be. The motivation for this is two fold: energy conservation and multiple usages. Measuring changes in the environment and passing this information to the PPM & CP needs to be done on a regular basis. Based on the WSN application, the WSN's nodes on-off duty cycle may not allow them to accurately measure the dynamics of the operational environment. Requiring the nodes to turn on solely to measure the environment could be counter productive in preserving the node's energy. Also, it is conceivable that in future industrial, commercial and public areas RF environment sensing networks will be needed to service multiple requirements such as providing RF measurements for multiple WSNs, WLANs and other wireless networks as well as addressing security requirements.

PPM & CP: The general concept for this functional block is to optimize the performance of WSNs based on the predicated operational characteristics of the WSN. The optimization is conducted off line and the operational changes are then downloaded to the network. An important constraint for the functional block is that the cost (i.e., energy consumption) required for updating the network needs to be less than the savings obtained by the performance improvement achieved by the update. To facilitate efficient network updates, *contingency planning* is used to develop a robust set of contingency policies for each node with each policy addressing a distinct variation in the observed RF interference environment.

Within a WSN there are often a rich set of routes between a source and a sink involving a varying number of hops. Contingency planning involves the development of a set of routes through a network with individual routes in the set having the same or nearly the same energy requirement, i.e., a *contingency policy*. Routes requiring lower total energy have a greater utility. In an interference free environment all routes between a source and a sink requiring the same number of hops expend approximately the same total energy. This is based on the WSN transmitters using a fixed transmit power level which is common with Bluetooth and IEEE 802.11 transceivers. Therefore the set of routes requiring the minimum number of hops would represent the most energy efficient contingency policy. In an operational environment with interference sources, certain routes may require an excessive number of retransmissions in order to complete one or more hops within the route. Under this condition, a new contingency policy is required. The new contingency policy is associated with the observed interference environment and removes the routes requiring excessive retransmissions from the set. Therefore, based on the approach presented in the paper, a contingency policy is triggered by a specific observed interference environment in order to avoid routes with excessive retransmissions. This is accomplished by working within the networks distributed routing protocol by providing the nodes affected by interference with a list of nodes to avoid within its one-hop neighborhood. Over time, as new interference environments are observed and incorporated into new contingency policies, the contingency plan becomes robust. The PPM & CP block can then update the network with the current optimal contingency policy based on the observed operational environment. It is also conceivable that over sufficiently long time intervals quasi-periodic behavior could be learned based on observing operational environment patterns. In these cases, the network nodes could automatically follow a sequence of contingency policies with limited interaction from the PPM & CP functional block.

Interference issues associated with WSN operation have been actively investigated. The focus of a number of researchers is on self-interference within a WSN and its impact on capacity [5] and on methods to mitigate [6]. Link quality aware routing has been proposed [7] [8]. The researchers' cognitive packet networks (CPN) approach uses an adaptive selection of paths. The technique uses specially designated packets, which learn how to achieve a predetermined routing goal. The results presented for CPN examine self-interference in an ad hoc network, even though the technique could be extended to include issues associated with coexistence, i.e., interference between two collocated and uncoordinated wireless networks as presented in this paper. The CPN approach is fully distributive and is based on a neural network learning algorithm. Packets are required to be exchanged within the network in order to learn the desired routing goal. The technique presented in this paper avoids the communication overhead associated with learning the state of the interference, by using the PPM & CP strategy outlined in Figure 1 and as presented in the remainder of this paper.

In the remainder of the paper, the PPM & CP approach is developed for optimizing energy efficiency within a multi-hop WSN by developing contingency plans for route management in dynamic interference environment. In Section II and III, a general formulation for the approach is developed. In Section IV, the approach is illustrated based on a Bluetooth WSN operating in an IEEE 802.11b interference environment. Conclusions and future work are presented in Section VI.

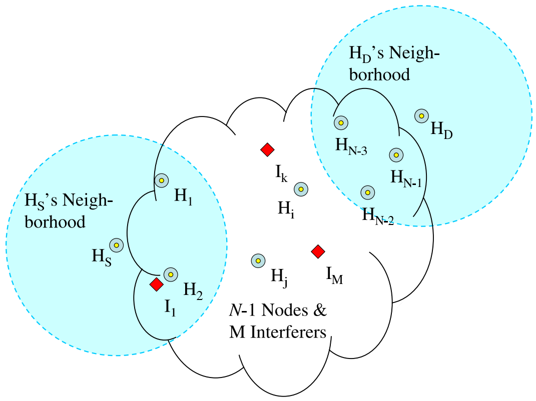

Fig. 2. General Network Topology for WSN in an operational environment with interference sources.

II. Route Management in a Dynamic Interference Environment

In this section, an approach for route management is developed within the context of the PPM and CP strategy depicted in Figure 1. The goal is to provide the WSN nodes with contingency plan updates based on observed spectrum usage patterns in order to minimize the energy required to transmit a packet from an arbitrary source node H_S to the destination node H_D. Within a WSN the destination node is often the base station at which the sensor data is collected. The PPM & CP block is divided into three stages for route management: parameter estimation, WSN performance assessment and optimization model, and contingency planning and WSN update strategy. Each of these stages are developed in greater detail in this section.

A. Parameter Estimation

The first stage in the PPM & CP is to estimate parameters required for evaluating and predicting the performance of the WSN based on the current operational environment. The operational environment is characterized by the RF environment sensing network which provides information concerning activity levels of the interference sources and estimates of signal power levels.

Figure 2 illustrates a general WSN network topology with $N-1$ nodes between the source node at H_S and destination node at H_D. In addition to the WSN nodes, there are M interference sources $I_1 ... I_M$. Based on a fixed transmission power and the RF propagation characteristics of the environment, each node can directly communicate with a set of nodes in its one-hop neighborhood and $U_i = \{H_{i1} H_{i2} ... H_{|U_i|}\}$ represents the set of nodes in H_i's one-hop neighborhood where $|U_i|$ is the cardinality of the set. For the study presented, a fixed energy ε is required for transmitting and receiving a single packet transmission within a node's neighborhood. Due to interference, packet retransmission could be required in order to successfully transmit a packet. Therefore, the expected energy required to transmit a packet from H_i to H_j is given by $\varepsilon \overline{N}_{Tx}(H_i, H_j)$ where $H_j \in U_i$ and

$$\overline{N}_{Tx}(H_i, H_j) = 1 + \frac{Pr[C|i,j]}{1 - Pr[C|i,j]} = \frac{1}{(1 - Pr[C|i,j])} \quad (1)$$

is the expected number of transmissions required to successfully transmit a packet from H_i to H_j. $Pr[C|i,j]$ is the probability of requiring a retransmission due to interference from one or more interference sources, i.e., probability of collision given by

$$Pr[C|i,j] = \sum_{k=1}^{M} Pr[C_k|i,j] - \sum_{l=1}^{M} \sum_{\substack{k=1 \\ k \neq l}}^{M} Pr[C_k|i,j] Pr[C_l|i,j] + ... \quad (2)$$

assuming the collision probabilities for each interference source I_k, $Pr[C_k|i,j]$, are independent. $Pr[C_k|i,j]$ is given by

$$Pr[C_k|i,j] = Pr[A_k] Pr[C_k|i,j,A_k] \quad (3)$$

where $Pr[A_k]$ is the probability the interference source is active and $Pr[C_k|i,j,A_k]$ is the probability of collision given the interference source is active. $Pr[C_k|i,j,A_k]$ takes into account the dynamics between the interference signal's characteristics and the desired signal's characteristics at the intended receiver, located at H_j .

The principle output required by the next stage in the PPM & CP is $\overline{N}_{Tx}(H_i, H_j)$ based on the observed interference environment characterized by the interference sources activity levels, $Pr[A_k]$. In order to evaluate $\overline{N}_{Tx}(H_i, H_j)$, based on (3) the collision probability $Pr[C_k|i,j,A_k]$ needs to model the specific interference scenario. For the scenario presented in Section III, a WSN based on Bluetooth technology is operated in an IEEE 802.11b WLAN environment. The collision probability is based on the likelihood the Bluetooth packet and IEEE 802.11b packet are time and frequency coincident with the interference signal having sufficient power to cause an error. Based on the author's previous work [9] [10], a near closed form solution was derived for evaluating $Pr[C_k|i,j,A_k]$. This result was used in the analysis presented in Section III. A detailed presentation of the derivation $Pr[C_k|i,j,A_k]$ goes beyond the scope of this paper, but for completeness the equation is given

$$Pr[C_k|i,j,A_k] = \frac{2Pr[C_T]}{B_{UL}} \times \eta \quad (4)$$

where

$$\eta = \int_0^{B_{UL}/2} \left(1 - \frac{1}{2} \left[erfc \left(\frac{\Omega_{I/S}(i,j,I_k) - \overline{\gamma}(f_{offset})}{\sqrt{2}\sigma_\gamma} \right) \right] \right) df_{offset}$$

where $Pr[C_T]$ is the probability of time coincidence between the IEEE 802.11b packet and Bluetooth packet and the term $\Omega_{I/S}(I,j,I_k)$ represents the interference to signal power ratio (I/S) in dB at the receiver located at H_j based on transmitter at H_i and interference source at I_k. The I/S ratio is given by

$$\Omega_{I/S}(i,j,I_k) = \Omega_{802} - \Omega_{BT} - 10 n log_{10} \left(\frac{Dist_E(H_j, I_k)}{Dist_E(H_j, H_i)} \right) \quad (5)$$

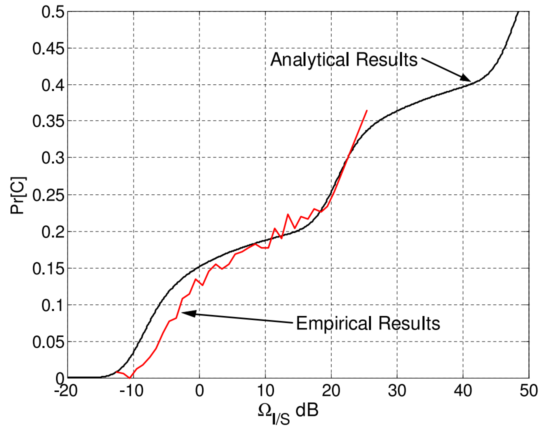

Fig. 3. Probability of collision versus interference to signal power ratio empirical and analytical results.

where $\Omega_{802} = 20dBm$ and $\Omega_{BT} = 0dBm$ are typical IEEE 802.11b and Bluetooth transmit powers, respectively, n is the path loss exponent, and $Dist_E(x, y)$ is the Euclidean distance between x and y. A graph of $Pr[C_k|\cdot]$ versus $\Omega_{I/S}(\cdot)$ based on (4) is given in Figure 3. As presented in [9] [10], empirical testing was conducted to validate (4) and the results of the empirical tests are graphed in Figure 3 for comparison.

B. WSN Performance Assessment and Optimization Model

The next step within the PPM & CP functional block is to use the parameter estimations for the number of transmissions, $\overline{N}_{Tx}(\cdot)$, to assess the WSN routing performance. The notation for the assessment procedure is developed based on Figure 2 as follows. Let the i^{th} route between source node H_S to the destination node H_D be defined as $R_{SD,i} \equiv [H_S H_{i1} H_{i2} ... H_{i(|R_{SD,i}|-1)} H_D]$ where $H_{i1} \in U_S$ (U_S is the one-hop neighborhood of the source node), $H_{i2} \in U_{i1}, ...$ and $|R_{SD,i}|$ represents the number of hops in route $R_{SD,i}$. An objective of route management is to minimize the energy expended by multi-hop packet routing. If there is no interference, then the routes that satisfy $|R_{SD,\min}| \equiv \min_i |R_{SD,i}|$ represent the optimal routes and the predicted energy for routing the packet would be $\varepsilon \times |R_{SD,\min}|$. As illustrated in Section IV, interference can significantly influence the set of minimum energy routes. By observing $Pr[A_k]$ for the interference sources and subsequently estimating $\overline{N}_{Tx}(H_i, H_j) \forall i, j$ based on (1) - (5), the predicted optimal route(s) would be the set of $R_{SD,i}$ which minimizes the total number of transmissions required to successfully transmit a packet, i.e., $\min_i \overline{N}_{Tx}(R_{SD,i})$ where

$$\overline{N}_{Tx}(R_{SD,i}) = \overline{N}_{Tx}(H_S, H_{i1}) + ... + \overline{N}_{Tx}(H_{i(|R_{SD,i}|-1)}, H_D) \tag{6}$$

and the expected energy required to route the packet is $\varepsilon \times \min_i(R_{SD,i})$.

In general, it is infeasible to use a centralized algorithm for determining a WSN multi-hop route. Therefore, using the centralized PPM & CP functional block to directly determine which routes to use within the WSN is impractical. The approach presented is based on using the PPM & CP to provide information to the WSN's nodes which will facilitate distributed computation of the most cost effective routes for successful transmissions in environments with multiple, non-stationary interference sources. To achieve the goal, we build upon the requirement of a number of current wireless ad hoc network routing algorithms that require one-hop neighborhoods' to be defined as an initial step in formulating a multi-hop route [11] [12] [13] [14] [15] [16] [17] [18]. Formulation of energy efficient routes can be facilitated by PPM & CP by biasing, i.e., weighting, the nodes in U_i based on the cost of the one-hop transmission.

In order to bias the one-hop neighborhoods, the WSN routing performance needs to be assessed by evaluating the WSN routes based on the observed interference activity within the RF environment. In order to achieve this goal, the predicted values of $N_{Tx}(R_{SD,i})$ for a given operational environment are used in conjunction with *Markov Decision Process* (MDP) [19] to develop a rank ordering for all $R_{SD,i}$. This process is repeated between all source and destination nodes. The MDP provides a ranked set of routes specified by

$$W_{SD}^{(q)} = \left[w_{SD,1}^{(q)}, ..., w_{SD,i}^{(q)}, w_{SD,i+1}^{(q)}, ..., w_{SD,|W_{SD}^{(q)}|}^{(q)} \right] \tag{7}$$

where $w_{SD,i}^{(q)}$ is the expected number of transmissions required for the i^{th} path from source to destination based on the q^{th} operational environment, i.e., $w_{SD,i}^{(q)} = \overline{N}_{Tx}(R_{SD,i})|\Psi^{(q)}$, $\Psi^{(q)}$ defines the q^{th} operational environment based on $\Psi^{(q)} \equiv [Pr[A_1], ...Pr[A_k], ..., Pr[A_M]]$, $|W_{SD}^{(q)}|$ is the number of routes in $W_{SD}^{(q)}$, and $w_{SD,i}^{(q)} \leq w_{SD,i+1}^{(q)}$. The MDP algorithm is briefly presented in Section III and key to its efficient utilization is the formulation of the contingency plan and WSN update strategy presented next.

C. Contingency Plan and Update Strategy

To further enhance the network update process, contingency planning [20] [21] [22] [23] [24] is used in the last stage of the PPM & CP functional block (Figure 1). Contingency planning is used to develop contingency policies to address the WSN operational requirements needed for the current environment. The contingency policy needs to work within the context of the WSN distributed routing protocol and needs to provide an efficient method for updating the WSN.

As indicated above, a contingency policy is used to modify the one-hop neighborhoods such that the WSN's distributed routing protocol avoids routes with high retransmission rates and uses routes with the minimum or near minimum retransmission requirements. From the MDP a ranked set of routes is provided, $W_{SD}^{(q)}$, where $w_{SD,1}^{(q)}$ represents the optimal route for the q^{th} operational environment, $\Psi^{(q)}$. Implementing the optimal route for each change in the operational environment is too costly. The contingency, therefore, specifies a set of actions required to work in conjunction with the WSN's distributed routing protocol. To illustrate the process, let the interference source I_1 have $Pr[A_1] = 1.0$ where the location of the sensor nodes and interference sources are given in Figure 2. Under this scenario the number of retransmissions between H_S to H_2 is large due to the proximity of I_1 to H_2. The action required by the contingency needs to reduce the likelihood of H_S routing through H_2 and an action required by the contingency policy is denoted by $U_S : H_2^-$. This action represents a negative weighting of the node H_2 within the one-hop neighborhood of H_S.

Based on the set of actions associated with the l^{th} contingency policy and based on the characteristics of the distributed routing protocol, a ranked listing of the routes between the source node and destination node can be identified as

$$\chi_{SD,l}^{(q)} = \left[w_{SD,l_1}^{(q)}, ..., w_{SD,l_i}^{(q)}, ..., w_{SD,l_{|\chi_{SD,l}^{(q)}|}}^{(q)} \right] \tag{8}$$

where $\chi_{SD,l}^{(q)}$ is a set of ranked routes resulting from the contingency policy's actions, $w_{SD,l_i}^{(q)} = \overline{N}_{Tx}(R_{SD,l_i})|\Psi^{(q)}$, $|\chi_{SD,l}^{(q)}|$ is the number of routes in $\chi_{SD,l}^{(q)}$, and $w_{SD,l_i}^{(q)} \leq w_{SD,l_{i+1}}^{(q)}$. The expected operational cost (energy), $O_{SD,l}^{(q)}$, required to route a packet from the source node to the destination node under the l^{th} contingency policy based on the q^{th} operational environment and assuming the routes in $\chi_{SD,l}^{(q)}$ are equilikely is

$$O_{SD,l}^{(q)} = \frac{1}{|\chi_{SD,l}^{(q)}|} \sum_{i=1}^{|\chi_{SD,l}^{(q)}|} w_{SD,l_i}^{(q)}. \tag{9}$$

Therefore, the optimal set of actions for the l^{th} contingency policy is to minimize $\chi_{SD,l}^{(q)}$ while also minimizing the number of actions required to implement the policy.

In addition, the operational cost is used in determining whether or not a new contingency policy is justified. Given a new operational environment is observed, Ψ^{New}, then a new contingency policy is formulated l_{New} with corresponding contingency policy's actions and expected operation cost $O_{SD,l_{New}}^{(New)}$. Associated with the new contingency policy is a energy cost required to update the WSN with the new policy, i.e., $P_{SD,l_{Best}}^{(New)}$. Therefore, in order to justify the cost of updating the WSN with the new contingency policy the following inequality must hold

$$\epsilon T_H^{New} \left[O_{SD,l_{Best}}^{(New)} - O_{SD,l_{New}}^{(New)} \right] > P_{SD,l_{New}}^{(New)} \tag{10}$$

where $O_{SD,l_{Best}}^{(New)}$ is the expected operational cost for the current best contingency policy l_{Best} and T_H^{New} is the time horizon for the operational environment Ψ^{New}, i.e., an estimate of the time interval over which operational environment remains essentially unchanged.

III. Route Assessment - Markov Decision Process

The contingency plans for the nodes in the WSN are developed by determining the optimal policy for each node at a given level of interference using a Markov decision process (MDP) [19]. An MDP is defined via its state set *S*, action set *A*, transition probability matrices *P*, and reward matrices *ρ*. On executing action *a* in state *s* the probability of transitioning to state $\acute{s}$ is denoted $P(\acute{s}\,|s,a)$ and the expected reward associated with that transition is denoted $\rho(\acute{s}\,|s,a)$.

A rule for choosing actions is called a *policy*. Formally it is a mapping π from the set of states *S* to the set of actions *A*. If an agent follows a fixed policy, then over many trials, it will receive an average total reward which is known as the *value* of the policy. In addition to computing the value of a policy averaged over all trials, we can also compute the value of a policy when it is executed starting in a particular state s. This is denoted $V^{\pi}(s)$ and it is the expected cumulative reward of executing policy π starting in state s. This can be written as

$$V^{\pi}(s) = E[r_{t+1} + r_{t+2}...|s_t = s, \pi] \tag{11}$$

where r_t is the reward received at time t, s_t is the state at time t, and the expectation is taken over the stochastic results of the agent's actions.

For any MDP, there exist one or more optimal policies which we will denote by π^* that maximize the expected value of the policy. All of these policies share the same optimal value function, which is written V^*. The optimal value function satisfies the Bellman equations [25]:

$$V^*(s) = \max_a \Sigma_{\acute{s}}\, P(\acute{s}\,|s,a)[\rho(\acute{s}\,|s,a) + V^*(\acute{s}\,)] \tag{12}$$

where $V^*(\acute{s})$ is the value of the resulting state $\acute{s}$. The sum on the right-hand-side is the expected value of the one step reward $R(\acute{s}\,|s,a)$ plus the value of the next state $\acute{s}$, which is the same as the backed-up value of a one-step lookahead search, and the max_a is choosing the action with the best backed-up value. This is the expected total reward that will be received by a node when action a is taken in state s and the node behaves optimally thereafter. Therefore, solving the MDP is tantamount to computing its optimal function.

Given an MDP model (S, A, P, R), a dynamic programming algorithm, value iteration, can be used to determine the optimal value function [26]. Value iteration works by computing the optimal value function assuming first a one-stage finite horizon, then a two-stage finite horizon and so on. These value functions are guaranteed to converge in the limit to the optimal value function. In addition, the policy associated with the successive value functions will converge to the optimal policy in a finite number of iterations [25] and in practice the convergence is quite rapid. The running time for each iteration is $O(|A||S|^2)$ and hence total running time is polynomial as long as the total number of iterations required is polynomial [27]. Starting with an initial guess, V_0, iterate for all s

$$V_{k+1}(s) = \max_a (\Sigma_{\acute{s}}\, P(\acute{s}\,|s,a)[\rho^a(\acute{s}\,|s,a) + V_k(\acute{s})]) \tag{13}$$

It is known that $max_{s\ \epsilon S}|V_{k+1}(s) - V^*(s)| \leq max_{s \epsilon S}|V_k(s) - V^*(s)|$ and therefore V_k converges to V^* as k goes to infinity. In practice, the value iteration algorithm iteratively updates the estimate of $V_{k+1}(s)$ based on the V_k values of neighboring states and stops when the update yields a difference that is below a threshold. The optimal policy is obtained by selecting the action with the highest value for each state.

To implement this approach in the WSN application, we first construct the control policy offline using generated data for the collision probabilities of node to node transmission for the given level of interference. The set of nodes describe the state space of the MDP. The neighborhood of each node defines the action space of each state and value is the utility accrued when the end node or a dead end is reached. We estimate transition probabilities of the form $P(x'|x,a)$, which denotes the probability of a transition to state x', given that the system was in state x and took action a. The transition probability is derived from the collision probability and represents the probability that the system was in x and took a and successfully arrived at x'. In our experiments we use a starting value of $V_0(s) = 0$ and a reward of -1 is given for each transmission allowing the reward measure to incorporate the expected number of transmissions such that the optimal policy in fact determines the optimal path from any node in the network to the end node.

This approach has several advantages over other methods. The policy is calculated for all expected interference scenarios in an offline manner which produces an ordered list of neighbors with weights giving significant information about neighbors for a given policy. This offline calculation means the nodes do not have to process data online, saving computational expense on the node level. Also, when the scenario changes only the nodes whose policy changes need to be updated. The policy is also forward looking, meaning it takes the entire route from the starting node to the end node into account. This global optimization means our result will be better or at least as good as any other method used.

IV. Illustrative Example

In this section, the following example is evaluated to illustrate the general PPM & CP strategy outlined in Section II and III for optimizing the WSN routing management in a dynamic interference environment. For the example, the WSN is based on Bluetooth [9] technology and the WSN operates in the presence of IEEE 802.11b [28] interference. The network topology for the analysis is given in Figure 4. Bluetooth nodes are located on a fixed grid at 3 meter intervals and are depicted as circles in Figure 4.

For the analysis presented, an exponential decaying path loss model is used for determining the received power [29]. Given path loss exponent, $n = 3$ and Bluetooth transmit power of $\Omega_{BT} = 0dBm$, Bluetooth nodes can reliably transmit $10m$. The neighborhoods for the source node, H_0, and destination node, H_{39}, are depicted in the figure by the two semi-circles (dashed lines). In the example presented, the single source to destination pair is considered in order to illustrate the process. The minimum number of hops required to transmit a packet from H_0 to H_{39} is 3, $|R_{SD}|_{\min} = 3$. Due to the relatively high degree of connectivity there are 33 routes requiring 3 hops (two are illustrated in the figure, $R_1 = [H_0, H_{19}, H_{20}, H_{39}]$

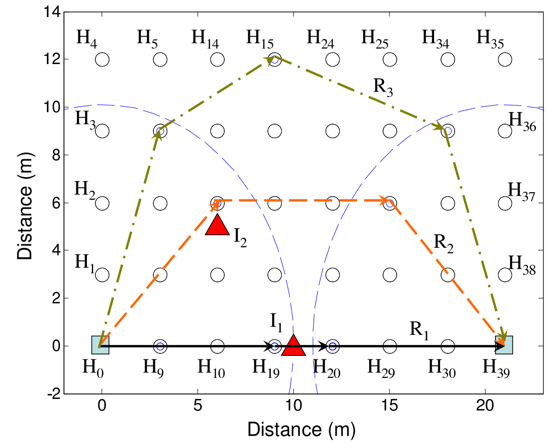

Fig. 4. Network Topology for Bluetooth WSN with IEEE 802.11b interference scenario.

and $R_2 = [H_0, H_{12}, H_{27}, H_{39}]$) and there are 1056 routes requiring 4 hops ($R_3 = [H_0, H_6, H_{15}, H_{33}, H_{39}]$ illustrates a 4 hop route). In this section the notation, $R_{SD,i}$ has been simplified to R_i. IEEE 802.11b interference sources are located at the triangles in Figure 4: I_1 at location [10, 0] and I_2 at location [6, 5].

Three scenarios are considered where each scenario examines a different number of interference sources. The scenarios are defined as follows:

- Scenario I: One IEEE 802.11b interference source at I_1,
- Scenario II: Two IEEE 802.11b interference sources - one at I_1 and one at I_2,
- Scenario III: Three IEEE 802.11b interference sources - two at I_1 and one at I_2 , For Scenario III, the two interference sources at I_1 are representative of an IEEE 802.11b access point with multiple transceivers operating in different frequency bands and utilizing a common antenna. Independence is assumed between the all interference sources.

For each scenario, a ranked set of routes $W^{(q)}$ was evaluated based on $\overline{N}_{Tx}(R_i)$. The Markov Decision Process (MDP) was used to create the policies and obtain the rank ordered paths for R_i. The MDP model representing system behavior for a particular environment is obtained from state set, action set, transition probabilities and a reward function. The state set is represented by a set of network nodes, the action set by the one hop neighbors, and the transition probabilities $Pr(s'|s,a)$. The reward function ρ uses the expected number of transmissions $\overline{N}_{Tx}(H_i, H_j)$. The ranked ordered paths for each R_i is determined by the MDP using the standard value iteration algorithm. According to [26], the expected cumulative reward (V) of taking action (a) from state (s) is calculated in terms of the cumulative reward of successor states via the recursive equation given by equation (13).

The algorithm iteratively updates the estimate of V(s, a) based on the maximum V value of neighboring states and stops when the update yields a difference that is below a threshold. Once value iteration is completed, the optimal path will be defined by the state that yielded the maximum V value for a given state. The V value obtained will be the optimal $\overline{N}_{Tx}$ for a given R_i. By observing all V values obtained from neighboring states an order list can be created that minimizes the $\overline{N}_{Tx}$ for a node, H_i, for each action in its neighbor set U_i. The MDP is run for each scenario presented and the resulting ordered lists present the best choices for transmission for a given scenario for each H_i.

For the example presented, the distributed routing protocol used within the WSN is based on a minimum energy routing protocol. Therefore, given no interference the 33 routes requiring 3-hopes require essentially the same energy to successfully transmit a message from H_0 to H_{39} . When a single IEEE 802.11b interference source is introduced at I_1, (Scenario I), then the expected energy required to successfully transmit a signal from the source to destination varies based on the relative impact the interference source has on the number of transmissions required for each route. A histogram of the expected number of transmissions $\overline{N}_{Tx}(\cdot)$ required for the 33 3-hop routes is shown in Figure 5. Based on the MDP analysis, the optimal route is $R_2 = [H_0, H_{12}, H_{27}, H_{39}]$ with $\overline{N}_{Tx}(R_2) = 4.08$. For the analysis presented, the baseline operational cost for routing the data assumes that the distributed routing protocol will select each of the 33 3-hop routes with equal likelihood. Using equation (9), the baseline operational cost $O^{(I)}_{SD,baseline} = 4.33$ where $O^{(I)}_{SD,baseline}$ is the baseline operational cost for the operational environment defined by Scenario I.

Within the PPM & CP functional block, the MDP provides a rank listing of the routes based on $\overline{N}_{Tx}(\cdot)$. The contingency policy for the operational environment is obtained by formulating a sequence of actions which reduce the likelihood of using high cost routes. Each action implemented incurs a cost for updating the WSN, therefore the following rule is employed for selecting the optimal set of actions to be used in formulating the l^{th} contingency policy

$$\frac{O^{(q)}_{SD,l(m)} - O^{(q)}_{SD,l(m+1)}}{O^{(q)}_{SD,l(m)}} > Thresh \qquad (14)$$

where $O^{(q)}_{SD,l(m)}$ is the operational cost based on equation (9) for the l^{th} contingency policy using the first m optimal actions and $O^{(q)}_{SD,l(m+1)}$ is the operational cost based on using the first $m+1$ optimal actions, and $Thresh$ is a threshold which is dependent on the operational conditions of the WSN. The threshold should be selected in order to ensure the justification of the new policy. Using (10), the following inequality needs to be satisfied $\forall l$

$$O^{(q)}_{SD,l} - O^{(q)}_{SD,new} > \frac{P^{(q)}_{SD,new}}{\epsilon T^{(q)}_H}. \qquad (15)$$

For Scenario I, the first optimal action is to reduce the likelihood H_0 transmits to its one-hop neighbor H_{19}, $U_0 : H^-_{19}$. For the analysis presented, $U_0 : H^-_{19}$ implies the distributed routing protocol removes H_{19} from U_0. In practice, this maybe too restrictive and simply reducing the likelihood of transmission maybe required in order to preserve connectivity within the network. By removing H_{19} from U_0, the seven highest cost routes are removed. The resulting operational cost based on this single action is $O^{(I)}_{SD,new} = 4.23$. This action provides a 2.2% improvement over the baseline. The next optimal contingency policy action is $U_{18} : H^-_{20}$. This results in $O^{(I)}_{SD,new} = 4.22$ based on a contingency policy which includes both Actions 1 and 2. The improvement using both actions is 2.4% or the marginal improvement provided by Action 2 over Action 1 is 0.2% . Table 1 summaries the first four optimal actions and their corresponding performance improvement. For illustrative purposes, using the requirement that the marginal improvement needs to be at least 0.5%, $Thresh = 0.5\%$, to justify an Action, then the contingency policy for Scenario I is limited to Action 1. In Figure 5, the removed routes and retained routes based on the optimal contigency policy are indicated in the histogram by lighter and darker shading, respectively. In order to justify the cost of updating the WSN with the new contigency policy $\left[O^{(q)}_{SD,baseline} - O^{(q)}_{SD,new}\right] = 0.094 > P^{(q)}_{SD,new}/\epsilon T^{(q)}_H$. If this inequality holds, then the nodes affected by the change would need to be updated with the new contingency policy.

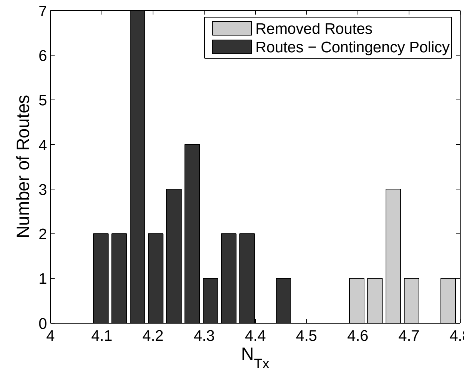

Fig. 5. Distribution of the Number of transmissions over the 3-Hop routes for Scenario I.

TABLE I

SCENARIO I - SUMMARY OF OPERATIONAL COSTS BASED ON SEQUENCE OF CONTINGENCY POLICY ACTIONS.

Scenario I	Action	Oper. Cost	Cumul. Improve.	Marginal Improve.
Baseline		4.33		
Action 1	$U_0 : H^-_{19}$	4.23	0.09 (2.2%)	0.094 (2.2%)
Action 2	$U_{18} : H^-_{20}$	4.22	0.10 (2.4%)	0.009 (0.2%)
Action 3	$U_{10} : H^-_{20}$	4.22	0.11 (2.6%)	0.007 (0.2%)
Action 4	$U_{11} : H^-_{20}$	4.21	0.12 (2.8%)	0.007 (0.2%)

The same approach was applied to evaluating the optimal contingency policy for Scenario II and III. For both of these scenarios the optimal route is $[H_0, H_9, H_{20}, H_{39}]$ with corresponding $\overline{N}_{Tx}(\cdot) = 5.42$ and $\overline{N}_{Tx}(\cdot) = 7.71$, respectively. Table II summarizes the sequence of optimal actions and corresponding operational costs and marginal improvements for both scenarios. Based on using $Thresh = 0.5\%$, for Scenario II the contingency policy requires the first 3 Actions and for Scenario III the contingency policy requires the first 6 Actions. Figures 6 and 7 depict histograms of $\overline{N}_{Tx}$ based on the 33 3-hop routes for Scenario II and Scenario III, respectively. Routes associated with the optimal contingency policy are shaded darker.

Table III provides an overall summary of the results for the three scenarios. Operational costs are presented for the baseline performance, i.e., all 3-hop routes are considered equilikely under the operational environment. Operational costs are also presented for the optimal contingency policy based on results given in Tables I and II. In addition, the minimum N_{Tx} based on the optimal route is provided for comparison. The goal of the PPM & CP functional block is to provide an overall improvement in the energy efficiency within the WSN. As can be observed from both Figures 6 and 7, for Scenarios II and III, the optimal contingency policies removed routes with lower N_{Tx} in order to reduce the number of actions required by the centralized PPM & CP functional block. Thereby, the overall energy efficiency is maximized by balancing the trade-off between minimizing the $\overline{N}_{Tx}$ required to route messages against the cost of implementing the policy.

TABLE II

SCENARIO II AND III - SUMMARY OF OPERATIONAL COSTS BASED ON SEQUENCE OF CONTINGENCY POLICY ACTIONS.

	Scenario II		Scenario III	
	Action	Oper. Cost (Mar. Imp.)	Action	Oper. Cost (Mar. Imp.)
Baseline		5.99		8.90
Action 1	$U_0 : H_{19}^-$	5.89 (1.60%)	$U_0 : H_{19}^-$	8.46 (5.00%)
Action 2	$U_0 : H_{12}^-$	5.80 (1.53%)	$U_0 : H_{12}^-$	8.35 (1.28%)
Action 3	$U_0 : H_{11}^-$	5.76 (0.78%)	$U_0 : H_{11}^-$	8.29 (0.70%)
Action 4	$U_{18} : H_{20}^-$	5.73 (0.37%)	$U_{18} : H_{20}^-$	8.23 (0.69%)
Action 5			$U_0 : H_{10}^-$	8.19 (0.55%)
Action 6			$U_{18} : H_{29}^-$	8.14 (0.58%)
Action 7			$U_0 : H_{07}^-$	8.12 (0.29%)

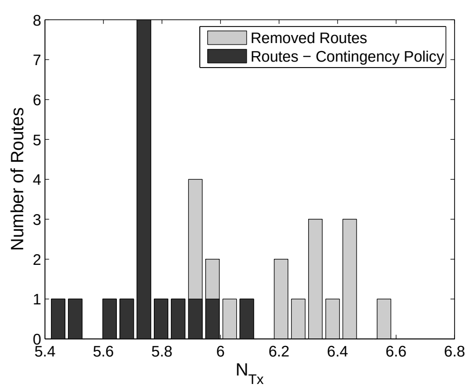

Fig. 6. Distribution of the Number of transmissions over the 3-Hop routes for Scenario II.

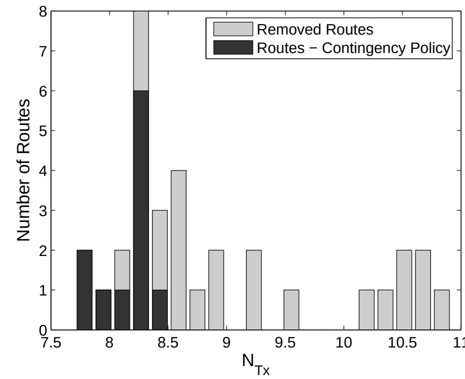

Fig. 7. Distribution of the Number of transmissions over the 3-Hop routes for Scenario III.

V. CONCLUSION AND FUTURE WORK

Energy consumption among the wireless devices participating in WSNs constrains the development and implementation of a broad range of applications. The PPM & CP methodology introduced in this paper provides a strategy for updating the operational mode of the WSN which minimizes energy utilization due to the time varying characteristics of the networks operational RF environment. An approach for using the PPM & CP strategy for optimizing the multi-hop routing was developed and shown to find the optimal routes. The advantage of using this approach was illustrated for a Bluetooth network in an IEEE 802.11b interference environment. By developing contingency plans off line for various scenarios we can minimize the updates needed when interference changes, only updating the nodes which have a change in their policy. In the long run this method will reduce the overall transmissions and lead to substantial energy savings.

In the future, we plan to investigate the effectiveness of the MDP based approach when the size of the WSN is scaled up to the order of 1000's of nodes. We plan to study methods where we can reduce overall policy computation costs by identifying similarity in scenarios before policy computation. This would facilitate computing policies for classes of scenarios instead of individual scenarios. Finally, we plan to investigate methods to make the centralized policy computation online. This might necessitate the need for a near-optimal policy instead of the optimal policy. We would like to study the trade offs of using

TABLE III

PERFORMANCE SUMMARY FOR THE THREE INTERFERENCE SCENARIOS

Scen.	Opt. Min N_{Tx}	Oper. Cost		% Improv. Over Baseline	
		Base-line	Opt. Cont. Policy	Opt. Cont. Policy	Opt. Min N_{Tx}
I	4.08	4.33	4.23	2.2	5.8
II	5.42	5.99	5.76	3.9	9.5
III	7.71	8.9	8.14	8.6	13.4

a near-optimal policy.

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