Dynamic Selection of Wireless/Powerline Links using Markov Decision Processes

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Abstract— **Communication networks for smart grids may consist of a mixture of legacy and new links using heterogeneous technologies, such as copper wires, optical fibers, wireless and powerline communication. If nodes are connected by two or more links, such as wireless and powerline, the sender of a message must decide on which link to transmit the next message. This paper considers the problem of dynamically selecting the link, based on success/failure (acknowledgement) of previous transmissions. The novel method is based on Markov (Gilbert-Elliott) channel models of lossy and time varying links. It specifies how to employ success/failure observations to rank the links optimally, with the objective function to maximize throughput. The theory of partially observable Markov decision problems (POMDP) provides the basic framework. We compare this new method with known linear learning strategies.**

I. Introduction

A. Heterogeneous Smart Grid Communication Networks

A Smart Grid consists of a diverse set of devices such as SCADA controllers, Ring Main Units (RMUs), Remote Terminal Units (RTUs), smart meters and routers. Consequently, smart grid communication networks are likely to use a variety of communication technologies, among them wireless and powerline communication (PLC) [11]. The existence of more than one communication technology increases redundancy and reliability. For this purpose networking stacks supporting multiple communication technologies are necessary to build a unified network [12], with a routing protocol that takes the characteristics of different communication technologies into account. As an example, imagine a network of devices that are capable of communicating not only over wireless links, but also over PLC. When one link is unavailable or faulty, the other should be used. For efficiency and power reasons, messages should not be transmitted on all links in parallel. Thus, a suitable routing solution requires automatic, transparent switching between the available communication interfaces depending on the state of the links.

B. Routing Protocol RPL and Link Metrics

The IETF Working Group Routing over Low power and Lossy networks (ROLL) has proposed an IPv6 Routing Protocol for Low-power and Lossy Networks (RPL, RFC 6550) [8]. In RPL, the most frequently used link metrics are delay, expected transmission count (ETX), energy consumption, and received signal strength. These metrics are measured and updated dynamically, in order to adapt the routing decisions to the time varying behaviour of the underlying links. Time constants of the link metric measurements and of the routing adaptation affect each other and determine the overall routing performance, but there is no well-defined coordination between these two processes. Link metric measurements are usually updated by some simple averaging, e.g. using some first order smoothing filter. When no packet transmission has occurred on a link, the last available measurement is used for routing.

In this paper we propose a new link metric update and link selection method. The new approach is to exploit the Markov properties of the underlying channel to derive an optimum method of updating the link metric and of selecting the best link, using the theory of Partially Observable Markov Decision Processes (POMDP). This is described in Section II and III. In order to assess this new method, we compare the new method with a known stochastic learning scheme in Section IV and V.

II. Communication Channels

A. Lossy and Time-Variant Channel Models

Finite State Markov Channels (FSMC) are simple models of time-varying communication channels [1], where the state transition probabilities characterize the dynamic behaviour of the channel. The simplest FSMC model is the well-known Gilbert-Elliott (GE) channel which has only two states 'good' (G) and 'bad' (B), with transition probabilities

$$\lambda_1 = \Pr\left(s_{t+1} = G \middle| s_t = G\right)$$
$$1-\lambda_1 = \Pr\left(s_{t+1} = B \middle| s_t = G\right)$$
$$\lambda_0 = \Pr\left(s_{t+1} = G \middle| s_t = B\right),$$
$$1-\lambda_0 = \Pr\left(s_{t+1} = B \middle| s_t = B\right).$$

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When the channel is in state $s_t \in \{G,B\}$, the data transmission success probability is p_G or p_B (with $p_G > p_B$), respectively [4]. If measurements of receiver signal levels or transmission success rates are available, an estimate of transition probabilities can be found by observing the mean duration times T_G and T_B (measured in multiples of the data transmission period) in which the channel is in the G and B state, respectively . Then,

$$1-\lambda_1 = \frac{1}{T_G}\text{, and } \lambda_0 = \frac{1}{T_B}.$$

This follows directly from the formula for mean sojourn times of Markov chains.

FSMC and GE models can be used to optimize data transmission under constraints: The data should be transmitted opportunistically when the channel is in a 'good' state. The theory of Markov Decision Processes (MDP) has been applied to derive optimum scheduling of data transmission. Details depend on whether the current channel state can be fully observed, which simplifies the prediction of the next states. [2] uses FSMC to do MDP with full state observation (i.e. channel state information is available) to optimize file transfer on a fading link.

Assuming that the underlying link layer performs acknowledged transmission, i.e. the transmitter obtains an acknowledgement if the transmission of a data packet has been successful, then the current state can at least be partially observed: If data transmission was successful ('ack'), the state was more likely in the 'good' state, while if no acknowledgement was obtained ('nak'), the state was more likely in a 'bad' state. Full state observation is only available under the special case of $p_G = 1$ and $p_B = 0$, and if the channel is actually employed for data transmission.

The Partially Observable Markov Decision Processes (POMDP) are in practice much more complex than MDPs, since they are based on a real-valued information state ('belief'), rather than on the finite number of states. [3] is an early paper using POMDP for transmit power control for wireless transmission. [7] uses POMDP to optimize transmission rate over a single GE channel. So called 'multi-armed bandit problems' consider the problem of optimally selecting one out of multiple channels over which to transmit, typically under the assumption of independent and stochastically identical channels [6]. The channel models described in the next section crucially do not satisfy this latter assumption, hence the simplifications in [6] are not applicable.

B. Wireless and Powerline Channel Characteristics

PLC is mainly affected by relatively slow processes such as switching of the power grid and activation of electrical equipment, hence level crossings or state transitions typically occur only every few hours [8][10]. Thus a powerline link 'PLC' is modelled as a GE channel with two states 'good' and 'bad', with low transition probabilities λ_0 and $1-\lambda_1$.

Typical wireless links in Smart Grid applications are fixed installations and operate in a steady state. Time varying behaviour occurs due to occasional shadowing, but these effects are typically measured in seconds or minutes, i.e. much faster than the time constants of the PLC link and are thus negligible. As a consequence, wireless links 'WL' are modelled simply by a constant average packet transmission success probability p_w (see Figure 1) when compared to PLC links.

These models for PLC and WL channels are obviously simplistic, but are chosen here to illustrate the basic concepts of our novel approach. Section VI discusses extensions.

III. Link Selection

A. Setting

In this section we derive the optimum policy π to select dynamically between the available links, such that the expected discounted total reward $R(s_t,a_t)$ over an infinite horizon,

$$V^{\pi}(s) = E_{\pi}\left[\sum_{t=0}^{\infty}\beta^t R(s_t,a_t)\middle| s_0 = s\right] \quad (1)$$

is maximized, where the actual reward $R_t = 1$ if the packet was transmitted successfully at time t, and $R_t = 0$ otherwise, and β is the discount factor ($0 < \beta < 1$). Discounting is appropriate if rewards in the future are less valuable, as is the case for delay sensitive communication.

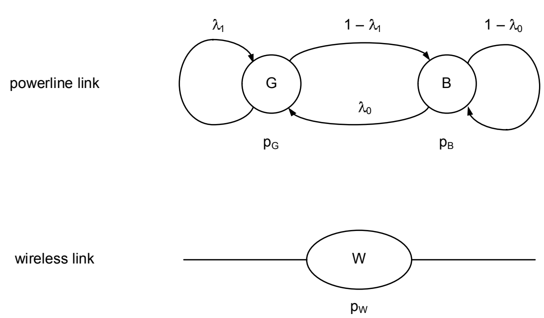

Figure 1: Link models: Gilbert-Elliott Markov model for powerline link (top), and single-state model for wireless link (bottom).

A policy π specifies the mapping from the channel observation $o_t \in \{$'*ack*', '*nak*'$\}$ to the action $a_t \in \{$'*PLC*', '*WL*'$\}$, taking the history of chosen actions and observations into account. In principle, the transmitter selects on which link to transmit a packet (action a_t), based on its current information, as represented by the so-called belief state $b(s_t)$, i.e. the probability that the powerline channel is in state s_t. Assuming that $p_B < p_W < p_G$, the transmitter should select '*PLC*' if the PLC link is in the 'good' state, since it has a higher success probability than the wireless link ($p_W < p_G$), and select '*WL*' otherwise. However, at time t of the transmission, the transmitter does not know the current state s_t of the links, but must predict it based on earlier observations o_{t-1} and using the Markov property of the channel. These observations are the confirmations ('acknowledgment' obtained by the underlying transmission protocol) whether a packet transmission has succeeded.

The proposed policy is as follows:

0. Initialize p, $0 \le p \le 1$. The scalar p represents the 'belief' that the PLC channel is in the 'good' state.
1. If $p \ge$ threshold p_{thr}
   transmit the data packet on the PLC link (a_t = '*PLC*')
   else
   transmit the data packet on the WL link (a_t = '*WL*').
2. If a_t = '*PLC*', wait for acknowledgement $o_t \in$ {'*ack*', '*nak*'}. If a_t = '*WL*', acknowledgements from the wireless protocol do not provide any observation of the state s_t of the PLC link, hence o_t = '*none'*.
3. (1.) If the transmission on the PLC link was successful (a_t = '*PLC*' and o_t = '*ack'*), update p as follows

$$p'_{ack} = \frac{\lambda_1 p_G p + \lambda_0 p_B (1-p)}{p_G p + p_B (1-p)}. \qquad (2)$$

   (2.) If the transmission on the PLC link was unsuccessful (a_t = '*PLC*' and o_t = '*nak'*), update p as follows

$$p'_{nak} = \frac{\lambda_1 (1-p_G) p + \lambda_0 (1-p_B)(1-p)}{(1-p_G) p + (1-p_B)(1-p)} \qquad (3)$$

   (3.) If the transmission was on the wireless link (a_t = '*WL*'), no new observation of the PLC link is available (o_t = '*none'*), and the belief on the PLC link state is simply propagated using the Markov transition probabilities as follows

$$p'_{none} = \lambda_1 p + \lambda_0 (1-p). \qquad (4)$$

   The proof of these update functions is given below.
4. $t := t + 1$ and loop to 1.

The determination of the threshold p_{thr} is crucial to the performance of this policy, and is given in the next section. Interpreting the 'belief' p as a novel link metric, the algorithm specifies how the transmitter updates the link metric and how to use it in an optimal manner.

B. POMDP Derivation of Optimum Policy.

The PLC link is modelled as a two-state Gilbert-Elliott channel, while the wireless channel WL is described by a single state, as shown in Figure 1. For the formal definition of the GE model, the assumptions and notations of [7] are used here. States are partially observable using the history of observations o_t and actions a_t, see Figure 2. An observation o_t = *ack* is a received acknowledgement message and the available actions are the transmission channels to be used.

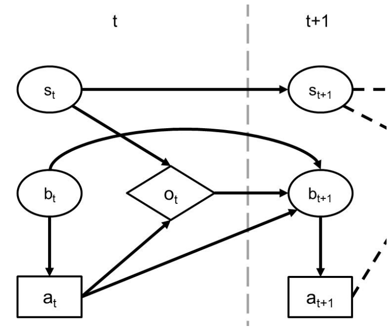

Figure 2: Causal relationships of PLC-WL problem in POMDP: states (s), actions (a), beliefs (b), observations (o) arrows depicting how they influence each other [5] (rewards are based on the observations and are omitted in the drawing).

The partial observation is captured by the *belief state b*, $b(s_t)=Pr(s_t | o_t, a_t)$, i.e. the a-posteriori distribution of s_t given the action a_t and the observation o_t (see below). $b(s_t)$ is an $|S|$-dimensional probability distribution over the state space S. For $|S|=2$, $b(s_t)$ can be represented by the scalar p,

$$\begin{aligned} p &= b(G) = \Pr(s_t = G, b) \\ b(B) &= \Pr(s_t = B, b) = 1 - p. \end{aligned} \qquad (5)$$

For Markov systems, the current belief state $b(s_t)$ is a sufficient statistic of the complete system history [5]. This property is key for the recursive form of the optimum policy.

<u>Reward:</u> The reward for action $a_t \in$ {'*PLC*', '*WL*'}, given the state $s_t \in$ {'*G*', '*B*'}, is given by the success probability of the transmission[1],

$$\begin{aligned} R(s_t = G, a_t = PLC) &= p_G \\ R(s_t = B, a_t = PLC) &= p_B, \end{aligned} \qquad (6)$$

$$R(a_t = WL) = p_W. \qquad (7)$$

The expected reward $R^b(b,a_t)$ is defined as,

$$R^b(b, a_t) = \sum_{s_t} \Pr(s_t, b) R(s_t, a_t) \qquad (8)$$

[1] The actual reward $R_t \in \{0,1\}$ is the successful transmission. The expected reward is $R(s_t,a_t) = E(R_t | s_t,a_t)$, where here the expectation is with respect to the channel noise, and is thus given by the success probabilities p_G, p_B, or p_W.

where the expectation is with respect to the belief states b. Here b is represented by the scalar p, hence

$$\begin{aligned} R^b(b, a_t = PLC) &= \Pr(s_t = G, b) R(s_t = G, a_t = PLC) \\ &+ \Pr(s_t = B, b) R(s_t = B, a_t = PLC) \\ &= p p_G + (1-p) p_B \end{aligned} \tag{9}$$

$$R^b(b, a_t = WL) = p_W \tag{10}$$

The belief state b_o^a resulting from b, after taking action a_t and observing o_t, is defined as

$$b_o^a = \Pr(s_{t+1} | b, a_t, o_t). \tag{11}$$

Proof of belief update equations (2) to (4): To prove (2), using Bayes' theorem,

$$\Pr(s_{t+1} = G | b, a_t, o_t = ack) = \frac{\Pr(s_{t+1} = G, b, a_t, o_t = ack)}{\Pr(o_t = ack | b, a_t)} \tag{12}$$

$$\Pr(s_{t+1} = G, b, a_t, o_t = ack) = \sum_{s_t} \Pr(s_{t+1} = G | s_t, a_t, o_t = ack) \Pr(o_t = ack | s_t, a_t) \Pr(s_t, b) \tag{13}$$

$$\begin{aligned} &\Pr(s_{t+1} = G, b, a_t = PLC, o_t = ack) = \\ &\Pr(s_{t+1} = G | s_t = G, o_t = ack) \Pr(o_t = ack | s_t = G) \\ &\Pr(s_t = G, b) + \Pr(s_{t+1} = G | s_t = B, o_t = ack) \\ &\Pr(o_t = ack | s_t = B) \Pr(s_t = B, b) = \\ &= \lambda_1 p_G p + \lambda_0 p_B (1-p) \end{aligned} \tag{14}$$

and similarly for the denominator in (12),

$$\Pr(o_t = ack | b, a_t) = \sum_{s_t} \Pr(o_t = ack | s_t, a_t) \Pr(s_t, b) \tag{15}$$

(2) is then obtained by inserting (14) and (15) into (12)□

Belief transition function: For fully observable states, the probability of the state s_{t+1} is calculated as

$$\Pr(s_{t+1} | s_t, a_t) = \sum_{o_t} \Pr(s_{t+1} | s_t, a_t, o_t) \Pr(o_t | s_t, a_t) \tag{16}$$

For partially observable Markov states, the belief state b' at the next time step $t+1$ is calculated by a generalization of (16)

$$\Pr(b' | b, a_t) = \sum_{o_t} \Pr(b' | b, a_t, o_t) \Pr(o_t | b, a_t) \tag{17}$$

Bellman equation: The value function $V^*(b)$ is defined as the maximized expected discounted reward $V^\pi(b)$, i.e. the reward achieved under the optimum policy π. From POMDP theory [5][7], $V^*(b)$ satisfies the Bellman equation

$$V^*(b) = \max_{a_t} \left\{ R^b(b, a_t) + \beta \sum_{b'} \Pr(b' | b, a_t) V^*(b') \right\} \tag{18}$$

The second term on the right hand side is the expected value function after the transition,

$$\begin{aligned} &\sum_{b'} \Pr(b' | b, a_t) V^*(b') \\ &\underbrace{=}_{b' = b_o^a} \sum_{s_{t+1}} \sum_{o_t} \Pr(s_{t+1} | b, a_t, o_t) \Pr(o_t | b, a_t) V^*(b_o^a) \\ &= \sum_{s_{t+1}} \sum_{o_t} \Pr(s_{t+1}, b, a_t, o_t) V^*(b_o^a). \end{aligned} \tag{19}$$

$\Pr(s_{t+1}, b, a_t, o_t)$ is given in (13), while (11) gives the belief update b_0^a. In the first equality in (19), the summation over b' is over the possible values of b_0^a. The Bellman (18) thus becomes

$$V^*(b) = \max_{a_t} \left\{ R^b(b, a_t) + \beta \sum_{s_{t+1}} \sum_{o_t} \Pr(s_{t+1}, b, a_t, o_t) V^*(b_o^a) \right\} \tag{20}$$

For the present case of two states $s_{t+1} \in \{'G', 'B'\}$ and two observations $o_t \in \{'ack', 'nak'\}$, there are 4 terms in the double sum in (19). Using (9), (10) and (14), the Bellman equation can be written explicitly as

$$V^*(p) = \max_{a_t \in \{PLC, WL\}} \left\{ \begin{array}{l} p p_G + (1-p) p_B + \\ + \beta \left(\begin{array}{l} (\lambda_1 p_G p + \lambda_0 p_B (1-p)) V^*(p'_{ack}) + \\ + (\lambda_1 (1-p_G) p + \lambda_0 (1-p_B)(1-p)) V^*(p'_{nak}) + \\ + ((1-\lambda_1) p_G p + (1-\lambda_0) p_B (1-p)) V^*(1-p'_{ack}) + \\ + ((1-\lambda_1)(1-p_G) p + (1-\lambda_0)(1-p_B)(1-p)) V^*(1-p'_{nak}) \end{array} \right), \\ p_W + \beta (p'_{none} V^*(p'_{none}) + (1-p'_{none}) V^*(1-p'_{none})) \end{array} \right\} \tag{21}$$

Note that the arguments of $V^*(\cdot)$ on the right hand side are nonlinear mappings of p. (21) is a condition on the desired function $V^*(\cdot)$. The function can be computed numerically, see below. The optimal action is then, for each given p,

$$a_t^* = \arg\max_{a_t} V^*(p). \tag{22}$$

Typically, the resulting optimum policy has the simple threshold form (see [7])

$$a_t^* = \begin{cases} PLC, & p \geq p_{thr} \\ WL, & p < p_{thr} \end{cases} \quad (23)$$

where p_{thr} is a threshold resulting from $V^*(p)$, and p is to be updated to p_{ack}', p_{nak}', or p_{none}' according to the observations, as given by (2) to (4).

Value Iteration: The Bellman equation (18) can be solved numerically by the Value Iteration algorithm (see e.g. [5]).

IV. Stochastic Learning

In order to assess the new optimum method derived above, it will be compared in Section V with a simple ad-hoc stochastic learning technique [9] described in the following: A learning automaton can choose from a finite number of actions and receives feedback (acknowledgment messages) depending on the state of the system and the action chosen. As the process progresses the automaton learns to select the optimal action for the current state asymptotically and adapt to state changes. If the transmission was successful, the probability to select the used strategy for the next transmission is increased, otherwise it is decreased. To make sure all strategies are tested from time to time, even when the connection is currently bad, there is an upper and lower limit on the probability. More precisely the proposed scheme (slightly modified to our setting) works as follows.

0. Initialize $p := 0.5$, $t:=1$. p represents the probability for choosing the PLC channel at time t.
1. Transmit the data packet on the PLC link with probability p, (a_t := '*PLC*'), and on the Wireless link otherwise, (a_t := '*WL*').
2. (1.) If the transmission on the PLC link was successful (a_t = '*PLC*' and o_t = *'ack'*), update p as follows: $p: = p + a(1-p-A)$;
   (2.) if the transmission on the PLC link was unsuccessful (a_t = '*PLC*' and o_t = *'nak'*), update p as follows: $p := p - b(p-B)$;
   (3.) if the transmission on the WL link was successful (a_t = '*WL*' and o_t = *'ack'*), update p as follows: $p:=p - a\ (p-B)$;
   (4.) if the transmission on the WL link was unsuccessful (a_t = '*WL*' and o_t = *'nak'*), update p as follows: $p:=p + b\ (1-p-A)$;
3. $t := t + 1$ and loop to 1.

The parameters a and b control the speed versus the accuracy of the algorithm and A and B control how close the selection probability gets to 0 and 1. When comparing the performance of this method to the belief method, we use the same parameter values as used in [9], a=b=0.3, A=B=0.003.

V. Comparison

The update mechanism for metrics such as ETX on which routing protocols like RPL are based is usually not specified, or depends on other network stack protocols like neighbor discovery and their configuration (e.g., when and how often messages are sent over which links). As a consequence of this decoupling of the metric and its update mechanism, the performance on GE channels can be suboptimum and will vary with configuration parameters that are not related to the metric.

We thus compare our approach only to stochastic learning which has been designed for such scenarios, rather than to more traditional metrics such as ETX. We study some scenarios with varying values for the state transition probabilities and channel transmission success rates λ_0, λ_1, p_G, p_B and p_{WL} for 1'000'000 time steps, executed 10 times. We compare the throughput (% of packets delivered) of the belief threshold and the learning algorithm with the throughput achievable by an algorithm which knows the channel state perfectly and therefore can choose the best action accordingly, and a random algorithm which chooses WL or PLC with probability 0.5.

Figures 3 and 4 show boxplots of the average success probabilities for a fast and a slow changing PLC channel, as described by their state transition rates.

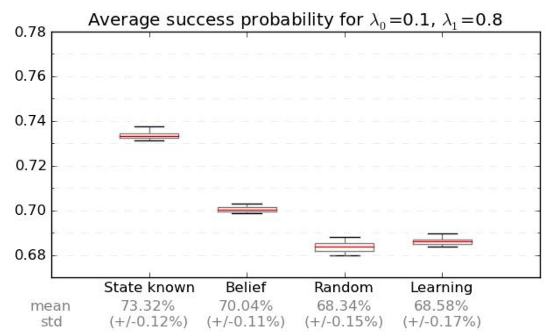

Figure 3: Average success probability for λ_0=0.1, λ_1=0.8, p_G,=0.8, p_B = 0.6 and p_{WL},=0.7.

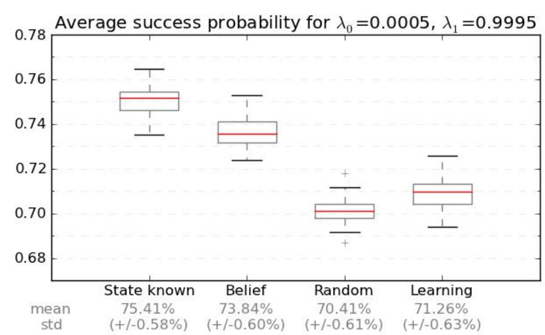

Figure 4: Average success probability for λ_0=0.0005, λ_1=0.9995, p_G,=0.8, p_B = 0.6 and p_{WL},=0.7.

Our experiments reveal that 1) the belief threshold algorithm performs very well if state changes are not frequent, e.g., λ_0=0.0005, λ_1=0.9995. (Assuming a transmission rate of 1 packet/s, e.g., λ_0 = 1–λ_1 = 0.001 models a channel which changes between the 'good' or 'bad' state only after on average 1000 sec.) 2) If the PLC channel is in the bad state and the belief has reached its lowest value λ_0, the algorithm increases the belief up to the threshold value and then usually drops back to almost λ_0, if the channel is still (or again) in the bad state, or jumps to the maximum value λ_1, if the channel is now in the good state (see Figure 5). 3) the probability to select PLC in the learning algorithm may be subject to much oscillation (see Figure 6) and by design never reaches 1. In Figure 5 one can see that at around time 160 the belief exceeds the threshold even though the channel is in the bad state. This happened because there were a few successful transmissions despite being in the bad state, which is not unusual for p_B = 0.6. Overall, the belief threshold algorithm performs best.

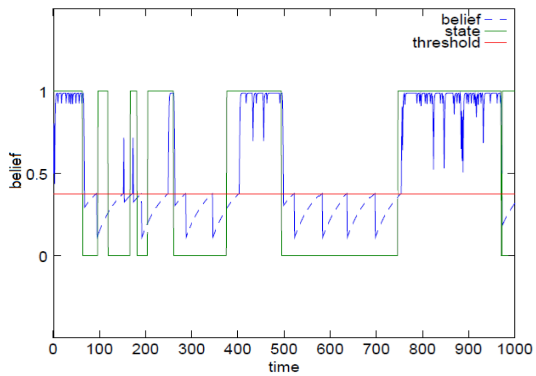

Figure 5: Example showing the state the PLC link (green line, good = 1, bad = 0) and the value of the belief (initialized at 0.5, dashed blue line). Channel parameters λ_0=0.01, λ_1=.99.

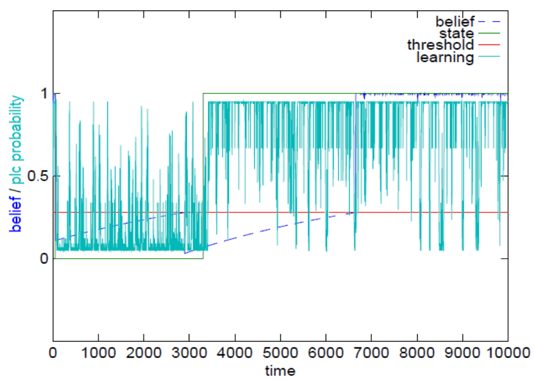

Figure 6: Example illustrating how the learning probability to use the PLC link oscillates while the belief is much more stable. Channel parameters λ_0=0.0001, λ_1=.9999.

VI. Conclusion

This paper has introduced a new approach for dynamic link selection, by applying Markov channel models and the theory of POMDP. Considering the belief state p as a link metric, the formulas for p given above provide a novel and optimum algorithm to define and update the metric used for link selection, and are thus an improvement over the state-of-the-art ad-hoc smoothing algorithms. This link metric is used in an optimum way for link selection, when more than one link is available between source and destination, and at least one of them is time-varying and lossy, to maximize the packet transmission throughput. The algorithm uses and requires knowledge of the parameters of the Markov models of the links. Coarse estimates for these parameters can be easily derived from measurements. Such coarse parameters are sufficient to achieve a noticeable improvement over state-of-the art ad-hoc schemes which do not include any quantitative characterization of the time-varying link behaviour. The POMDP method can in principle be extended to the cases with several links, each modelled by an FSMC. Given these models, the POMDP approach yields the optimum policy. However, due to the high number of states, the optimum policy becomes more complex than the simple threshold scheme described above for the two state GE model.

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