Assessment of Proactive Transmission Power Control for Wireless Sensor Networks

Roshan Kotian
Technische Universiteit Eindhoven
Den Dolech 2, 5612 AZ
The Netherlands
r.kotian@tue.nl

Georgios Exarchakos
Technische Universiteit Eindhoven
Den Dolech 2, 5612 AZ
The Netherlands
g.exarchakos@tue.nl

Antonio Liotta
Technische Universiteit Eindhoven
Den Dolech 2, 5612 AZ
The Netherlands
a.liotta@tue.nl

ABSTRACT

In order to prolong lifetime of Wireless Sensor Networks (WSN), Transmission Power Control (TPC) techniques are employed. The existing TPC schemes adjust the transmission power mostly reacting to changes at link quality between communicating nodes. Proactive TPC has been proposed in the recent past as reactivity does not address the need for reliability. Efficiency of a proactive TPC is determined by its prediction accuracy to link quality, ease of configuration and energy efficiency. Current state-of-the-art does not argue about proactive TPC methods on those requirements. This paper provides a targeted analysis of four prominent algorithms such as Discrete Kalman Filter (DKF), Exponentially Weighted Moving Average (EWMA), Simple Moving Average (SMA), Weighted Moving Average (WMA), and Linear Regression (LR) that could be employed in a proactive low-power TPC technique. Our experiments indicate that prediction accuracy of DKF has the least forecasting error and outperforms the prediction accuracy of all other algorithms under discussion. Amongst the Moving Average algorithms, the prediction accuracy of WMA is significantly better and linear regression algorithm has the worst performance. Evaluating the cost involved in terms of radio power and ease of configuration, WMA is the best algorithm for implementing proactive TPC.

Categories and Subject Descriptors

C.4 [Performance of Systems]: *Performance Attributes*; C.2.1 [Computer-Communication Networks]: Network Architecture and Design – *Wireless Communication*;

General Terms

Algorithms, Performance, Reliability, and Prediction.

Keywords

Transmission Power Control, Kalman Filter, Moving Average, Linear Regression, RSSI, PRR, Prediction, and IEEE 802.15.4.

1. INTRODUCTION

Low-power wireless sensor networks operate in uncertain indoor or outdoor environments. The uncertainty in the channel significantly reduces the communication reliability. Fall in the reliability also has other adverse effects such as reduction in the lifetime of the node as packets may have to be retransmitted. Transmission Power Control (TPC) techniques adjust the transmission power to ensure good communication link quality, but avoid energy waste.

A TPC technique is considered lightweight and efficient if (a) it has minimal communication overhead,(b) instantly and accurately perceives or even predicts the variation in link quality, and (c) consumes as less energy as possible. Although many TPC techniques have been proposed in the recent past, they do not completely fulfil the criteria above. In addition, there is a need for TPC algorithms to be intelligent enough to cope with uncertainties in the environment [18]. Designing TPC with above-mentioned criteria and implementing it on top of protocols such as CG-AODV [9][23]can greatly increase the reliability of sensor networks.

Drastic variations of link quality in indoor and outdoor WSN deployments, has for long motivated the need for TPC. Inteferences in indoor dense low power lossy WSNs coming from e.g. WiFi or microwave ovens frequently impede the link quality [2]. Temperature at outdoor deployments reduces the efficiency of the radio chip [3] which, in combination with humidity, impacts the link quality [27][30].

To handle those rapid changes of the channel conditions, most of the TPC schemes employ a heavy initialization phase. That is, every transmitting node frequently broadcasts to help TPC determine the link quality. This reactive approach falls short of the main objective – minimizing power consumption. Communication has a higher impact on energy consumption than computation for most of the sensor nodes. CC2420 radio chip consumes 17.4 mA at full power [8][1].

Devising a low-power proactive TPC technique that forecasts the link quality instantly and accurately solves two main problems:

1. Communication overhead is reduced drastically because fewer messages need to be sent in the initialization phase as the TPC can predict the future link quality on a per-packet basis.

2. Energy consumption is reduced because less broadcast packets are sent and, by forecasting link quality, nodes can communicate with one another with optimum power level.

The higher the accuracy of the link quality prediction, the bigger the savings on communication overhead and energy are. Moreover, the ease of configuration refers to fine-tuning the parameters to improve the prediction accuracy. If the TPC algorithm has certain parameters that need to be tweaked to enhance the prediction accuracy, then the system must undergo trial and error phase before the network becomes operational. Having the sensor network with small operational phase is desirable.

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To the best of our knowledge, there are no studies assessing the performance of various potential transmission power predictors suitable for low-power IEEE 802.15.4 protocol family. Therefore, the main objective of this paper is to provide comprehensive prediction accuracy analysis and ease of configuration of various algorithms such as Simple Moving Average, Weighted Moving Average, Linear Regression, and Kalman Filter. These algorithms like [5][6] are chosen because they are not complex and can be implemented in the resource scarce sensor nodes.

The rest of the paper is organized as follows. In Section 2, we provide the related work. Section 3 provides the information about the experimental setup. Section 4 briefly introduces the algorithms evaluated. Section 5 provides the performance evaluation in terms of prediction accuracy of the algorithms in discussion. In Section 6, we summarize and conclude the paper.

2. RELATED WORK

In literature, we broadly find two categories of transmit power control strategies – reactive and proactive. In reactive-based approaches, the transmit power level is adjusted when the link quality metrics such as Received Signal Strength Indicator (RSSI), Packet Reception Rate (PRR), Signal-to-Noise Ratio (SNR), etc., attain a certain threshold. In proactive-based approaches, the choice of transmit power level is estimated by acquiring the knowledge of the varying channel condition before the packet is transmitted [20].

In [11], the receiving node (R_x) instructs the transmitting node (T_x) to increase the power level after the fall in the RSSI. The drawback of this approach is that the reliability is compromised since R_x takes corrective actions only after the packet is sent. This is also the case with ODTPC[14]. Moreover, R_x approximates the transmission power to use while communicating with T_x based on the RSSI value of the received packet from T_x. ODTPC assumes that all the link quality between nodes are symmetric. But in fact, the links between the nodes are asymmetric [2]. This approach clearly has not considered temporal aspects (impact of time) while designing a TPC that may compromise the communication reliability of the network.

However, the advantage of these methods are that they do not have initialization phase as in ATPC[16] where all transmitting nodes send a broadcast message to all of its neighboring nodes for all the power levels. Since, the communication channel varies quite often; the initialization phase has to be executed repeatedly.

In order to overcome demerits of utilizing initialization phase and predict the fall of RSSI beforehand, [20] proposed AODTPC, a Kalman filter- based TPC algorithm. Although the inventors of AODTPC demonstrated better performance compared to ODTPC and ATPC, more statistical investigation is necessary to predict forecast error. Though AODTPC achieves a good accuracy with a low energy footprint, tuning Kalman filter is not an easy-to-automate task.

Next, we provide necessary reasoning of using appropriate link quality metric as an input parameter to the algorithms under test. Many parameters such as SNR, Packet-Counting (PC), Required Number of Packet Transmissions (RNP), Link Quality Indicator (LQI), RSSI, and PRR have been used in the recent past to analyze the link quality.

While PRR is a ratio of packet-based quantities (number of received packets over number of transmitted packets), RSSI measures the received signal strength. T_x can generate PRR of a link by observing over a time window the amount of packets transmitted from T_x and received by R_x of that link. The smaller that window is, the less accurate the metric becomes. For instance, using just the last two packets transmitted, PRR can take one of the three values: 0, 0.5 or 1. However, the requirement for instant prediction does not allow for very long periods or observation. Utilizing PRR as an input parameter to TPC algorithm may compromise the reliability of the network as it takes certain amount of time before T_x can estimate an appropriate power level.

[29] conducted experiments to gauge the performance of SMA, EWMA and Yule-Walker Predictor by providing it with Signal-to-Noise Ratio (SNR) data from an indoor setting with IEEE 802.11b/g enabled radios. Though SNR is a better link quality parameter than RSSI [25], the calculation of SNR requires both the received signal strength and the noise power at the receiver. Therefore, use of SNR entails extra computation and energy costs.

PC metric calculates the packet success rate by calculating the ratio of the number of successful packet transmissions to the total number of transmissions [29]. RNP parameter is the number of transmitted and retransmitted data packets during an estimated window divided by the number of successfully received packet minus 1 [7]. In order to compute PC and RNP, R_x nodes must have substantial amount of packets from the T_x nodes. Hence the TPC technique that utilizes these metrics turns out to be reactive and does not respond to the channel conditions instantly.

LQI on the other hand does not provide intermediate link quality due to its high variance [25]. The notion that RSSI is a bad link quality indicator is refuted by [13]. Furthermore, in [26] experiments indicate that the RSSI provides better estimate of link quality. Furthermore, RSSI allows for very small observation windows as well as online prediction algorithms. RSSI does not rely on multiple receptions but is calculated per received packet when the R_x is anyway active. Therefore, RSSI balances energy efficiency with prediction accuracy and timeliness. Due to its ease of availability, RSSI has widely been used in various WSN problem domains such as predicting battery depletion of sensor nodes [15] etc.

3. EXPERIMENTAL SETUP

In order to check the reliability of the prediction algorithm, it is necessary to collect the sensor link quality data in spatially varying real-world scenarios.

We performed the experiments using CrossBow TelosB motes running TinyOS and having CC2420 radio chipset in two different real-world scenarios such as [2]

- Connected Region: Here the link quality between the sensors is often good and stable
- Transitional Region: In this region, link between the sensors is very unstable and hence unreliable.

According to [31][2] the extent of transitional region depends on the environment such as indoor, outdoor and the radio hardware characteristics such as transmission power. Hence, the connected and transitional regions for our experiments were achieved by varying distance between the transmitting (T_x) and receiving (R_x) nodes in indoor and outdoor settings. The deployments were in actual office and street environments with little object mobility but high human mobility. This provided us the platform to check the prediction accuracy of the selected algorithms.

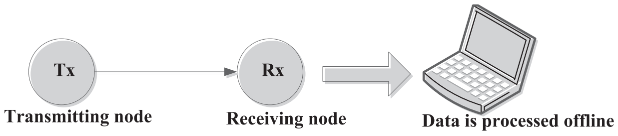

Figure 1: Represents the system overview

Figure1 represents the system setup that was used for the experiment. The data from T_x is received by R_x and transferred to a laptop. The laptop contains various algorithms that forecast the quality of the link offline.

Table 1 provides the distance between T_x and R_x and from the ground.

For the transitional indoor region (scenario 1), the distance between T_x and R_x was set to 11.50 meters. Height of the T_x and R_x from the ground was set to 0.5 meter and 1 meter from the ground respectively.

For the transitional outdoor region (scenario 2), the distance between T_x and R_x was set to 18.70 meters. Height of the T_x and R_x from the ground was set to 0.5 meter and 1.5 meters from the ground.

In the connected indoor region (scenario 3), the distance between T_x and R_x was set to 5 meters. Height of the T_x and R_x from the ground was set to 0.6 meter.

The height and distance between T_x and R_x in the connected outdoor region (scenario 4), was set to 0.8 meter from the ground and 8.7 meters respectively.

The distance between the sensors from the ground and each other were chosen randomly to match the realistic WSN deployment.

Table 1: Distance of T_x from R_x and both from the ground

Distance Region	T_x from R_x	T_x from ground	R_x from ground
Transitional Indoor	11.50m	0.5m	1m
Transitional Outdoor	18.70m	0.5m	1.5m
Connected Indoor	5m	0.6m	0.6m
Connected Outdoor	8.7m	0.8m	0.8m

Finally, the following settings were kept constant for the entire experiments

1. For every one second, T_x node was configured to send 28 bytes of data to R_x on the default channel 26 as specified by CC2420 for two minutes.

2. Default maximum transmission power level of 31 as specified by CC2420 was used by the T_x. This power level corresponds to 0dBm.

3. Battery power of T_x and R_x node was set to 3Volts.

4. Once the position of T_x and R_x was set, their position was not altered during the course of nodes sending the packets. Thus, we have used static sensor network.

5. Algorithms under discussion were run on normal laptops off-line.

We used RSSI for analyzing the link quality between the nodes. In CC2420, the RSSI is calculated over eight symbols and stores the result in RSSI.RSSI_VAL register [28].

Texas Instrument uses the following formula to calculate the Received signal power in dBm

$$P = RSSI\_VAL + RSSI\_OFFSET$$

Empirically it is found that RSSI_OFFSET value is set to -45 dBm [28].

4. CHARACTERISTICS OF INPUT DATA

Figures 2-3 provide the histogram of received signal strength index (bin size of 5 dBm) derived from 120 packets transmitted over two minutes.

From the Figure 2-3 and Table 2, we can infer that the variation in RSSI is significant for at least two regions –Transitional Indoor and Outdoor. This is an indication that the channel condition can vary instantly and there is a genuine need to forecast the link quality and adjust the power level to ensure good communication reliability.

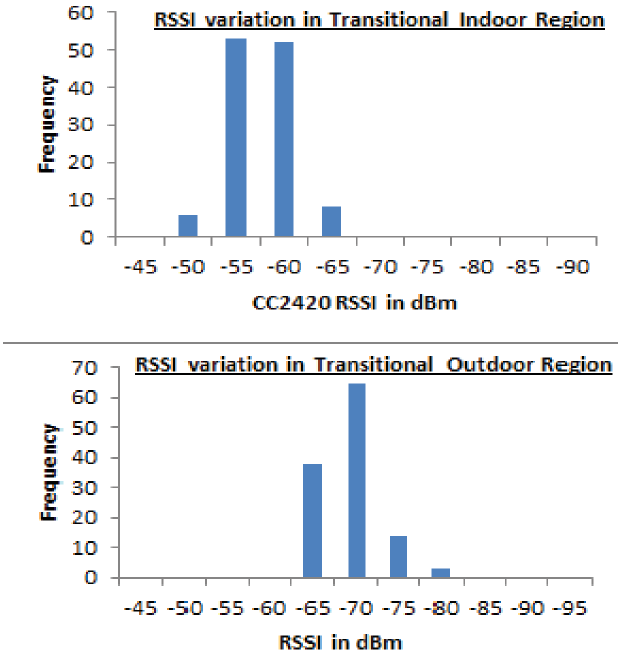

Figure 2: Histogram of RSSI in Transitional Region

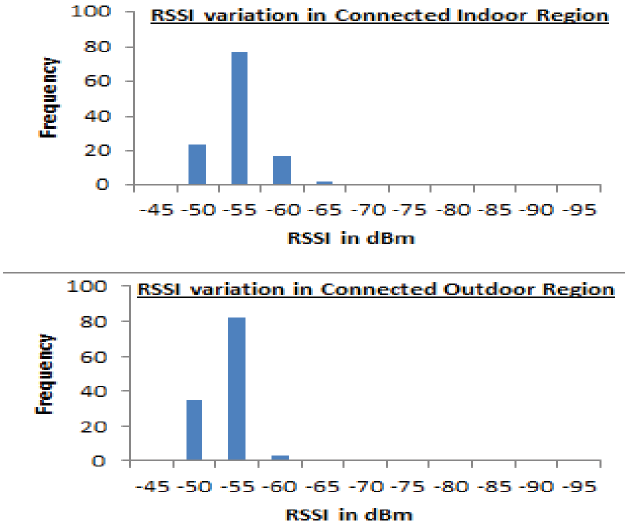

Figure 3: Histogram of RSSI in Connected Region

Table 2: Standard Deviation and Variance of RSSI values

Region	Stdev	Var
Transitional Indoor	2.62	6.86
Transitional Outdoor	3.4	12.24
Connected Indoor	2.7	7.5
Connected Outdoor	2	4.5

5. ALGORITHMS EVALUATED

In this section, we briefly explain five algorithms that can be used in TPC. All the methods below use collected actual RSSI values (X_i) to forecast the next RSSI value at any time slot t, $\hat{X}_t$.

1. Simple Moving Average (SMA) [21]**:** Is the unweighted mean of the last N RSSI values. The next RSSI value is forecasted by summing the series of past RSSI values.

$$\hat{X}_t = \frac{X_{t-1} + X_{t-2} + X_{t-3} + \cdots X_{t-N}}{N}$$

X_{t-i} is the past RSSI value at time $t-i$ where, $1 \leq i \leq N$.

2. Weighted Moving Average (WMA): Applies weight to all past N RSSI linearly. This implies that the latest RSSI values X_{t-1}, X_{t-2} …, X_{t-N} are given more weightage and has impact that is more significant on the average value than the previous RSSI values.

$$\frac{N * X_{t-1} + (N-1) * X_{t-2} + \cdots + X_{t-N}}{N + (N-1) + \cdots + 1}$$

3. Exponential Weighted Moving Average (EWMA) [10]**:** Similar to WMA; EWMA is weighted average of the last N RSSI values. However, the weight decreases exponentially with each incoming RSSI.

$$\hat{X}_t = \alpha(X_{t-1}) + (1-\alpha)S_{t-1}$$

Here, $\hat{X}_t$ is the value of RSSI at time slot t, S_t is the exponential moving average at time t. α is a smoothing factor and can take values between $0 \leq \alpha \leq 1$. By choosing appropriate α value, EWMA can be made sensitive to a small variation in RSSI.

4. Linear Regression (LR) [22] is used for modelling the relationship between a dependent variable (RSSI values X_{t-1}) and an independent variable (time). Mathematically LR is represented as:

$$\hat{X}_t = \beta_1 X_{t-1} + \cdots + \beta_N X_{t-N} + \varepsilon_i \ ; i = 1,2,\ldots,N$$

Here, β is the regression co-efficient and ε_i is the noise in the measurement.

5. Kalman Filter (KL) [12]**:** For static wireless network, the value of RSSI was modelled by[24] as

$$\hat{X}_t = X_{t-1} + W_{t-1}$$
$$\hat{Z}_t = \hat{X}_t + V_t$$

Where $\hat{X}_t$ represents the RSSI at time slot t and $\hat{Z}_t$ is the RSSI measurement calculated when the packet is received at time slot t. The noise in the process of X_t and the measurement noise in Z_t is modelled as Gaussian processes $W_{t-1} \sim N(0, Q)$ and $V_t \sim N(0, R)$ respectively. The value of Q is the variance of the RSSI values of the broadcast messages sent by sensor nodes during the initialization process. R is the variance of the measurement noise in dBm calculated by the sensor nodes before the transmission.

6. PERFORMANCE EVALUATION

As discussed earlier, WSN does not operate in a deterministic environment[17]. Therefore, the algorithms used in proactive TPC must be robust enough to forecast the behavior of the link quality. In order to evaluate the prediction accuracy of the algorithms mentioned in section 4, following statistical formulas are used.

Mean Absolute Percentage Error (MAPE) is the summation of the absolute difference of forecasted values $\hat{X}_t$ and eventual outcomes X_i divided by total number of N RSSI values. The value of MAPE ranges from zero to infinity. A predictor having MAPE value of zero is considered an ideal prediction algorithm. MAPE is represented as

$$\frac{100}{N}\sum_{i=1}^{N}\left|\frac{X_t - \hat{X}_t}{N}\right|$$

Mean Forecast Error (MFE): MFE is an indicator of forecasting bias and is calculated as

$$\sum_{i=1}^{N}\left|\frac{X_t - \hat{X}_t}{N}\right|$$

An ideal MFE would be zero. If MFE is greater than zero, it indicates that the prediction algorithm has under-forecasted and if MFE is less than zero, the prediction algorithm has over-forecasted.

Root Mean Square Error (RMSE): Calculates the standard deviation of the differences between the observed values X_t and predicted values $\hat{X}_t$. It is calculated as

$$\sqrt{\sum_{t=1}^{N}\frac{\left(X_t - \hat{X}_t\right)^2}{N}}$$

Large errors in the forecast have more impact on the value of RMSE than the small errors. RMSE takes a value between zeroes to infinity. The estimating algorithm having a RMSE of value zero is known to be ideal.

The assessed algorithms were configured as follows

1. N is initialized as the total number of RSSI values of each data packets minus the total number of training RSSI values of corresponding data packets.

2. β the regression coefficient for the linear regression was calculated from the RSSI values corresponding to the 30 and 20 data packets respectively.

6.1 Performance of SMA and WMA

Table 3 provides the prediction accuracy of SMA and WMA in three different scenarios (refer Table 1 to know about different scenarios). Two periods and three periods in the Tables (3-5) represent the RSSI values of corresponding data packets required by the algorithms before predicting the subsequent RSSI values. Periods also refer to the training data sample.

Table 3: Prediction Errors of SMA and WMA

Algorithms	Accuracy Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2 period SMA	MAPE	2.04	1.28	3.68	3.11
	MFE	-0.04	0.09	-0.06	-0.03
	RMSE	1.81	1.46	2.95	2.34
2 period WMA	MAPE	2.05	1.21	3.74	3.03
	MFE	-0.04	0.08	-0.06	-0.02
	RMSE	1.86	1.40	2.94	2.32
3 period SMA	MAPE	1.99	1.37	0.16	3.23
	MFE	-0.05	0.12	-0.06	-0.04
	RMSE	1.77	1.56	2.74	2.38
3 period WMA	MAPE	1.99	1.29	3.47	3.08
	MFE	-0.04	0.10	-0.05	-0.03
	RMSE	1.79	1.45	2.78	2.31

From Table 3 we can infer that the 3 periods WMA performs slightly better than its counterparts in various spatially and temporally varying scenarios. The statistical values indicate that the forecasting accuracy of the moving average algorithm in TPC can be enhanced by increasing the number of periods and by providing more weightage to the latest RSSI values. Increasing the number of periods means all the sensor nodes must perform initialization phase wherein each sensor node broadcasts packets equal to the number of periods before the actual communication. This brings in latency in the dense sensor network and increases the power consumption.

6.2 Performance of EWMA

Table 4 provides the comparison between EWMA with different smoothing factor (α) values for various scenarios.

Table 4: Prediction Errors of EWMA

Algorithms	Accuracy Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
2 period EWMA (α=0.6)	MAPE	2.06	1.28	2.96	3.68
	MFE	-0.07	0.09	-0.03	-0.06
	RMSE	1.84	0.30	2.24	2.95
2 period EWMA (α=0.94)	MAPE	2.2	1.15	3.04	3.99
	MFE	-0.03	0.06	-0.01	-0.04
	RMSE	2.08	1.37	2.43	3.12

As we can understand from Table 4, increasing the smoothing factor α does not necessarily improve the prediction accuracy. The reason for this is that if we give α value closer to one, more weightage is given only to the recent dataset. The choice of having appropriate smoothing factor is often a difficult task and it determines the accuracy of EWMA. [19] provides the necessary details to choose the smoothing factor. Like SMA and WMA, EWMA with smoothing factors 0.6 and 0.94 utilizes minimal amount of packets during the initialization phase. But the prediction accuracy of two period EWMA with α=0.94 and α=0.6 is not good compared to the SMA and WMA. Although, power consumption is kept to minimum, as the algorithm does not require implicit calculation of SNR, obtaining appropriate α value is not straightforward and needs more trial and error approach. Hence, when it comes to ease of configuration, EWMA falls short.

6.3 Performance of Linear Regression

From Table 5 we can infer that the linear regression has the worst performance.

Table 5: Prediction Errors of Linear Regression with β calculated from 30 RSSI values

Algorithms	Accuracy Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Linear Regression	MAPE	12.70	10.01	8.51	12.82
	MFE	7.80	-6.45	4.55	6.88
	RMSE	8.78	8.61	5.36	8.19

While testing the prediction accuracy of linear regression, we found that considerable amount of RSSI values are required (more than 30 packets) before predicting future RSSI values with minimum statistical errors. As shown in Table 6, any packets less than 30, significantly increases the statistical errors.

Table 6: Prediction Errors of Linear Regression with β calculated from 20 RSSI values

Algorithms	Accuracy Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Linear Regression	MAPE	20.57	12.25	28.05	14.90
	MFE	12.71	-8.44	15.91	8.16
	RMSE	14.53	10.87	17.52	9.72

The reason behind the bad performance lies on the line fitting to the already available RSSI values that does not update the slope has the new data arrived. In order to improve the accuracy we need a mechanism such as sliding window [4] that aids in updating the slope, as new data points are available.

6.4 Performance of Discrete Kalman Filter

From Table 7 we can conclude that Discrete Kalman filter gives the best accuracy in different realistic scenarios when compared to all the algorithms discussed. Three packets were made available (3 period) to Kalman filter before predicting the future RSSI values. To get the accurate prediction as seen in the Table 6, every node must calculate the variance in noise. To calculate the variance in the noise, R_x node needs to compute noise floor, hence the Rx node must be in listening mode for longer duration. This could be considered as a demerit of using Kalman filter.

Table 7: Prediction Errors of Kalman Filter

Algorithms	Accuracy Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Discrete Kalman Filter	MAPE	0.80	0.10	3.73	3.53
	MFE	-0.03	0.02	-0.11	-0.09
	RMSE	0.91	0.26	3.26	2.62

7. CONCLUSIONS

In this paper, we highlighted the major drawback of existing TPC that takes reactive approach to adjust the power level of the transmitting nodes. To overcome the drawbacks of reactive TPC, proactive TPC such as AODTPC [20] is proposed in the literature.

As mentioned in the section 1, an efficient proactive TPC has minimum communication and configuration overhead, accurately predicts the link quality and consumes less power during its execution.

In this paper, we evaluated above mentioned criteria for four prominent algorithms in spatially varying realistic environment. Testing in three different environmental settings, we found that Discrete Kalman Filter has the best accuracy and linear regression has the worst performance compared to the other algorithms.

Although Kalman Filter has best accuracy in finding the future link quality with minimum communication and configuration overhead, it needs the variance of the noise floor that can be obtained from SNR. Computing SNR involves high cost in terms of communication power because the radio must be kept in listening mode for prolonged period. Therefore, the power consumption of Discrete Kalman Filter is comparatively higher than the other algorithms.

EWMA is the third best algorithm in terms of forecasting accuracy because it does not outperform SMA and WMA. The smoothing factor α plays a crucial role in the efficiency of EWMA and configuring it is not a straightforward approach. Hence, the network must be put through a testing phase before it is deployed to get appropriate α value.

The accuracy of WMA is lower than that of Discrete Kalman Filter. However, this can be improved by marginally (two or three packets) increasing the packets broadcasted in the initialization phase. Given the cost of power consumption involved in Discrete Kalman Filter and prolonged configuration phase involved in enhancing the prediction accuracy of EWMA, we find WMA to be the optimal algorithm to be utilized in proactive TPC for resource constraint sensor nodes.

We discussed the importance of accurately predicting the variations in the channel condition. However, predicting specific power level to compensate the variations occurred at particular instance remains a challenge. In our future work, we would like to address this issue.

8. ACKNOWLEDGEMENTS

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