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An empirical investigation based quality of service aware transmission power prediction in low power networks

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Abstract. In low-energy networks, energy consumption is a significant concern. The adjustment of transmission power can save considerable energy at nodes during communication. The commonly used power control schemes maintain the transmission power based on the received signal strength indicator (RSSI) that depends on the interference in the environment. It is necessary to consider interference for retaining the lowest transmission power since low-energy network signals are vulnerable to interference changes. The earlier investigations suggested only linear models for power prediction in low-power networks. Hence, this paper investigates a classification-based transmission power prediction approach with the presence of interference. The approach works for linear and non-linear models based on RSSI, link quality indicator, neighbour node distance, and receiver power to maintain reliable communication with low energy consumption. The experiments were conducted in natural environments with common interference causes such as the human body, concrete walls, trees, and metallic bodies. The performance of the approach is analyzed with different prediction algorithms such as regression and classification. The investigation results demonstrate that it is possible to build a classification-based power prediction for linear and non-linear models by considering different spatial effects with 99% accuracy.

Keywords. Transmission power control; power prediction; RSSI; LQI; low power networks.

1. Introduction

Wireless sensor communication and IoT-based applications are becoming vital in our everyday life [1]. This type of network is organized with tiny battery-powered devices. These devices are prone to power constraints since most IoT applications are deployed for the long term without battery replacement [2]. The efficient utilization of available energy will increase life and reduce the power consumption of IoT networks. Due to this, power management stands as a challenge in low-power networks. The research in IoT network energy management is happening in two different directions, namely, energy harvesting techniques and energy-conserving techniques [3]. Generating energy from human body temperature in body area network, energy generation modules based on natural resources, etc., were proposed in different literature [4]. This technique uses a separate energy generation module as part of existing network hardware. The second energy-conserving approach reduces power consumption through optimized energy management in different network activities. Various power management schemes have been proposed so far by modifying physical layer parameters, link layer parameters, and network layer parameters [5]. One of the physical layer approaches is based on the transmission power control (TPC) technique.

The environments with the deployment of IoT networks vary based on the applications such as military, medical care, home automation, etc. Due to the node power constraints and the changing environmental conditions, reliable communication in a low-power network becomes difficult. The communication reliability can increase by using maximum transmission power at each node. But this will cause an increase in power consumption at each node, even though it is not necessary to use such high energy. One of the fascinating features of radio hardware used for next generation low-power networks [6] is changing the transmission power dynamically. The power level can be adjusted by modifying the registry which holds the power details. This feature can reduce the transmission energy by the intelligent selection of transmit power in each node during the communication.

TPC in the low power network is a cross-layer approach since the power level details are physical layer parameters. The modifications can happen at the medium access control or the network layer. Dynamic TPC means dynamically

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setting the minimum transmission power level without compromising the link quality. The commonly used link quality estimators in low power network communication are RSSI and link quality indicator (LQI). In this paper, a detailed investigation is conducted on the variation of RSSI and LQI in the presence of obstacles at different power levels and distances. The evaluation of the investigation is performed in natural environments such as indoors and outdoors. The experiments were conducted with common obstacles like the human body, metallic surface, and concrete walls. A data set is built with two-node communication.

The existing power control algorithms use linear equations to predict optimal transmission power. But in real environments, getting a linear relationship between communication quality and transmit power is not practical. The present work proposes a classification-based predictive model that envisages the power level needed for reliable communication with the neighbouring node. We used the data set built from the real-time experiments. The communication quality is set based on real-time experiments concerning the parameters such as LQI and RSSI. The experimental results show that the proposed approach performs well with an accuracy of 99%.

The rest of the paper is organized as follows. Section 2 summarizes the various research works done in TPC. The proposed model, the experimental setup, and the discussion of the results are given in sections 3 and 4, respectively. The conclusions are given in section 5.

2. Energy management in low power networks - An overview

Sensor networks are always prone to energy usage since they are battery-powered devices [7]. The research works in this area can be categorized into two energy harvesting techniques and energy conserving practices. Energy harvesting techniques focus on powering the IoT nodes by using different energy-generating circuits. The works vary based on the energy generation circuits like solar, tidal, human body temperature, etc., depending on the deployment environments [4]. The energy-conserving techniques try to utilize the available energy intelligently. The works investigated in this area are in the network layer, physical layer, and sleep-wake-up-based works [8].

The network layer based solutions add energy management techniques in routing protocols [9]. As per the works of [10–12], they found that energy usage can be reduced while routing since there are low energy paths from source to destination. In the sleep wake-up technique, a duty cycling mechanism minimizes energy usage. The node is kept in a sleep mode when it is not in an active state and is made to wake up only during the functioning time. Carrano *et al* [13] have explored a detailed survey on duty cycling techniques for managing energy consumption. They have divided these works into synchronous, semi-synchronous and asynchronous. The common problem in the sleep wake-up method is network latency.

In physical layer approaches, the reduction in energy consumption is investigated by efficiently managing transmission power. The work can be employed for dynamic power management in a communication system. In traditional IEEE 802.15.4 MAC protocol [14], each node uses the same transmission power level with maximum available power for communicating with other nodes. If two communicating nodes are near each other, there is no need to use high power to send packets. The power level can be managed so that it is enough to guarantee the communication quality so that the transmission energy can be saved.

In most of the research works, a feedback-based mechanism is adopted to manage power levels. The transmission power is adjusted based on the parameter link reliability [15], calculated based on the acknowledgement packet during transmission. Each node decides an optimal power level by sending a query packet at distinct power levels. The power level is set based on the acknowledgement received. A receiver-oriented approach is presented in P-TPC [16], where the receiver selects the transmit power. The metric used is packet delivery ratio (PDR) which counts the number of failed transmissions. Here, the transmission power for future transmission is set based on the PDR threshold value.

The works carried out in [5, 17, 18] use link quality as the metric to select the desired power level. Many researchers used these metrics as quality parameters since RSSI and LQI are readily available from the physical layer. In the work [18], the adaptive power management is used by collecting RSSI values using probe packets. Here, LQI is used along with RSSI as the quality parameter to improve communication quality.

All the discussed proposals work based on the probe message and its acknowledgement. The node sends these messages for each power level and increases the number of service messages and the network load. In order to overcome this issue, the earlier works [19–24] proposed an analytical model of TPC. Subsequently, a Q-learning based TPC is proposed in [19]. Initially, the transmission power is set as a minimum and changes according to the reward and penalty. In [20], the channel is modeled based on the finite state Markov model, and dynamic programming is used to control the transmission power.

Different fuzzy-based TPC schemes are presented in [21–24]. In [21], the transmission power is controlled by a fuzzy logic controller. Here, the input is RSSI, LQI, Signal to Noice Ratio (SNR), and data transmission rate. Another fuzzy-based approach stated in [22] uses a fuzzy system to adjust transmission power by maintaining dynamic topology control. A fast converging fuzzy power controller (FPC) is proposed in [23] and uses SINR and current transmission power as the input. Predictive TPC approach is proposed in [24]. This work predicts future RSSI variations using the grey model, and the transmission power is determined using a fuzzy inference system.

Another approach in dynamic power modeling is a real testbed based model. In this model, real-time experiments were conducted to study the environmental impact of transmission quality. These works are significantly less when compared with the above literature. ATPC stated in [25], is the latest work happened in that direction. Here the authors have conducted experiments in three different environments, and the collected data is used to model the transmission power. The curve fitting approach is used to model the system. A combination of RSSI and LQI is used for describing communication quality. This scheme is more reliable than others since the network behaviour differs in different environmental conditions. The environment with Wi-Fi signals and manually placed obstacles were considered for this experiment. Hence, the effect of interference is also reflected in the model. Here, the power modeling is viewed as a classification problem, and receiver power is used as a prediction metric. The contributions of the present work are as follows. 1) A real-time empirical investigation with the interferences introduced manually (Wi-Fi, human, concrete wall, and trees equipped environment) is conducted to build the data set. 2) The impact of the interferences and transmission power level on the communication quality is evaluated by varying distances and the data set built from the experiment. 3) Classification-based power level prediction approach is proposed and evaluated with linear and significantly non-linear models using a data set built from natural environments. 4) The performance comparison of different prediction algorithms such as multi-linear regression, KNN, Naive Bayes, and SVM in the collected data set is analyzed to suggest the suitability of the algorithm by considering the different spatial effects for better accuracy.

3. Proposed system

The communication quality among low power nodes is affected by the surrounding environmental factors such as environmental changes, background obstacles, the distance between sender and receiver, etc. Real-time experiments for investigating the impact of these parameters are conducted in the present work. The parameters selected for investigation are RSSI and LQI to measure the quality of communication. RSSI measures how well a receiver can hear a signal from the sender and is measured in −dBm with a scale of 0-100.

The detailed explanation of the proposed model is shown in figure 1. The experiment is first conducted in a plane ground without any obstacles. Secondly, the investigation experimented with barriers to show the impact of obstacles

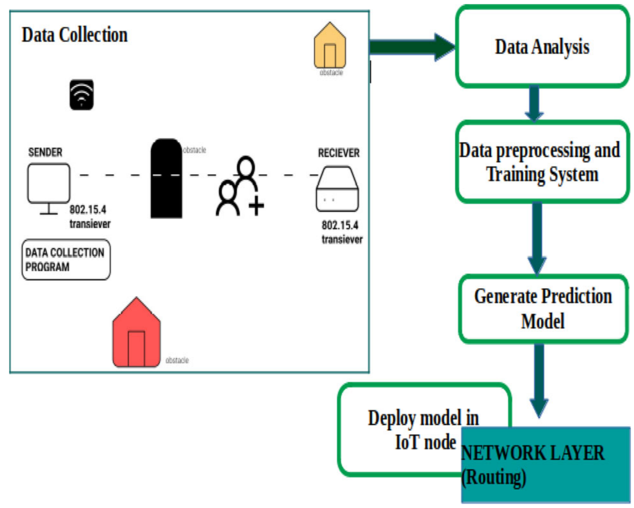


Figure 1. Proposed system.

on communication quality. Finally, a model is trained with data collected from the real environment, as shown in figures 2, and 3. The data is prepossessed and normalized to avoid any possible errors. The generated model can predict the most efficient route in terms of power consumption. The prediction is made in the nodes and computed for the efficient transmission power for the given LQI and RSSI. Thus, it is less computationally intensive and does not affect the node's energy performance.

4. Experimental results and evaluations

This section explains the study conducted, the analysis of parameters collected from different environments with different configurations, and the framing of the prediction model. The comparison analysis of previous works with the present work is shown in table 1.

Figure 2. Experiments on Indoor.

Figure 3. Experiments on Outdoor.

4.1 *A study conducted on environmental impact*

The experiments are done in two different environments: indoor and outdoor, as shown in figure 2 and 3, respectively, to understand the influence of environmental conditions on communication quality. IEEE 802.15.4 - Digi RF modules are used as the transmitter and receiver node. These nodes are placed in different locations with the same antenna direction. The selected indoor environment was a college campus corridor with obstacles such as Wi-Fi, concrete walls, and human. The outdoor considered is also equipped with obstacles such as humans, Wi-Fi, and trees. The RSSI and LQI are recorded with varying power level combinations in the varied distance. The sender node sends 100 packets in each combination, and the receiver records RSSI and LQI for each successful transmission.

Figures 2 and 3 show the data collection environment from where the data are collected. For this study, receiver power, transmitter power, and distance are varied during the communication. In the previous studies on RF communication [25], studies happened in different transmit power in the static distance. They have not mentioned the effect of transmit-receiver power combinations with distance in communication quality. Obstacles were placed manually in the communication path, and the selected environment was Wi-Fi enabled. The effect of reflection and scattering is also reflected in the collected data. Digi transceiver nodes are used here, and node power is divided into four different levels, power level 1 (−3 dBm), power level 2 (+2 dBm), power level 3 (+8 dBm), and power level 4 (+10 dBm) [27].

The LQI is computed in terms of the error in the received packets from the start of the frame delimiter measured with a scale of 0-255 in dBm. The value is calculated using the packet's physical layer header length and service data unit fields. The correlation value of the first 8 symbols is calculated for each received packet. The LQI is computed using the equation as follows.

Table 1. Comparison with previous work.

Author	Simulation/ Realtime	Scheme	Feedback based	Prediction Model	Features used for prediction	Interference Aware
Sabitha et al. [26]	Realtime	Select Tp based on predicted RSSI .	Yes	Markov-based prediction model	Previous RSSI values	No
Lee et al. [24]	Simulation	Select TP based on predicted RSSI	Yes	Grey prediction model	Previous RSSI values	No
Lin et al. [25]	Realtime	TP Prediction	Yes	Linear Regression	RSSI, LQI	No
Proposed Work	Realtime	TP Prediction	No	Classification	RSSI, LQI, distance, Receiver Power	Yes

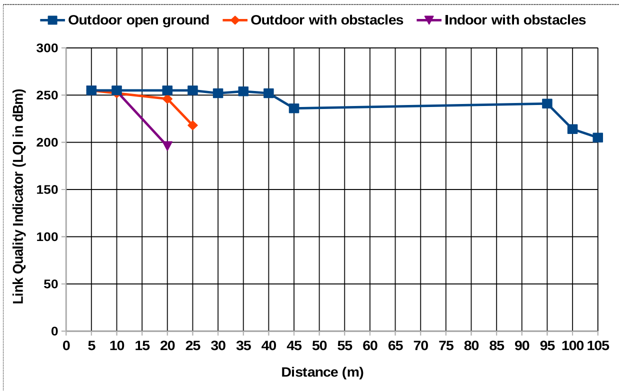


Figure 4. Link quality variation in different environments.

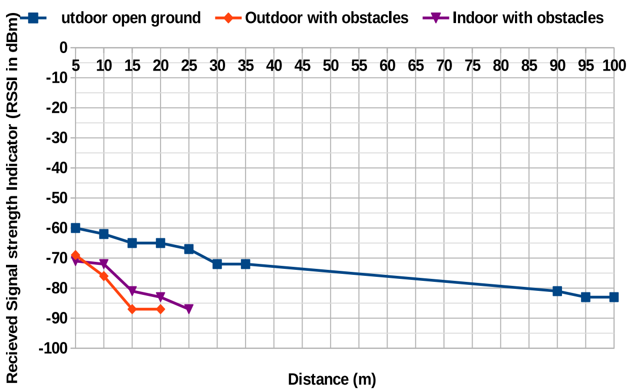


Figure 5. RSSI variation in different environments.

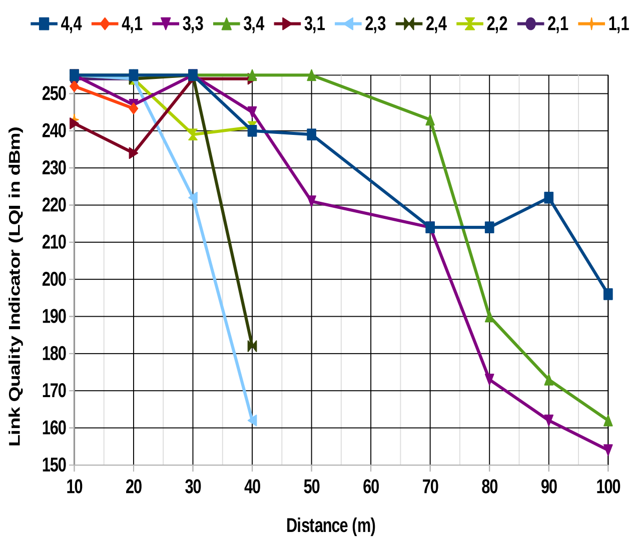


Figure 6. LQI variations in outdoor (with obstacles) with respect to different power level combinations.

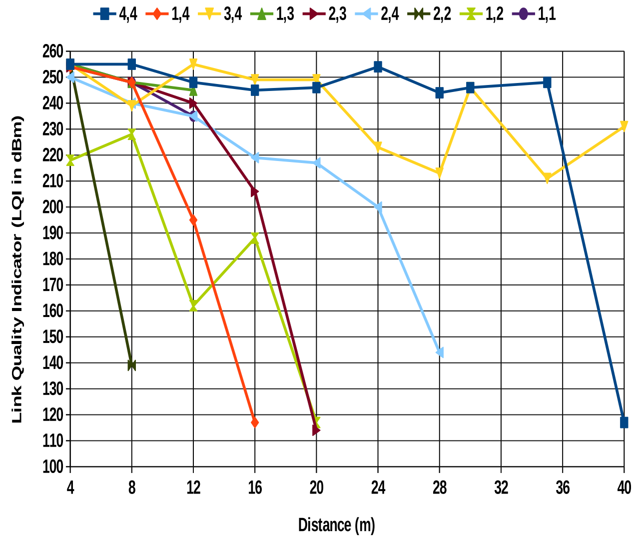


Figure 7. LQI variations in Indoor (with obstacles) with respect to different power level combinations.

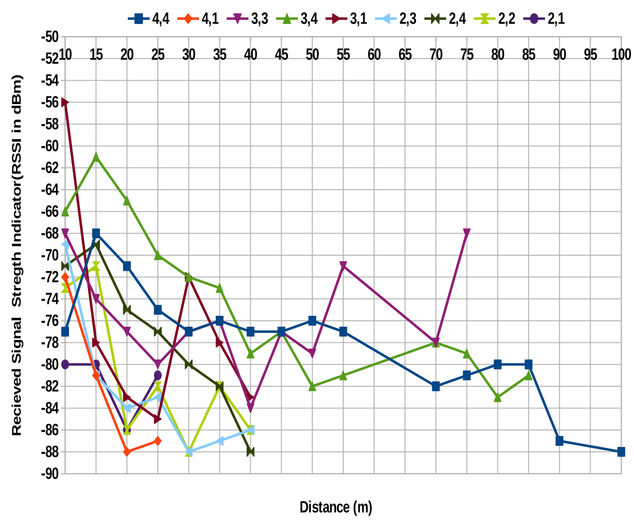


Figure 8. RSSI variations in outdoor (with obstacles) with respect to different power level combinations.

$$LQI = (CORR - a) * b$$

where *CORR* is the computed correlation value, and a and b are hardware-specific constants. Here, CC2420 is used as the transceiver unit, the values of a and b are considered as 40, and 110 [28].

Figures 4–9 shown here indicate the data collected from one communication pair. Each curve represents the variation of RSSI and LQI concerning the distance in different environments. Figure 4, 5 shows the behaviour of RSSI and LQI in the three environments. Outdoor with obstacles,

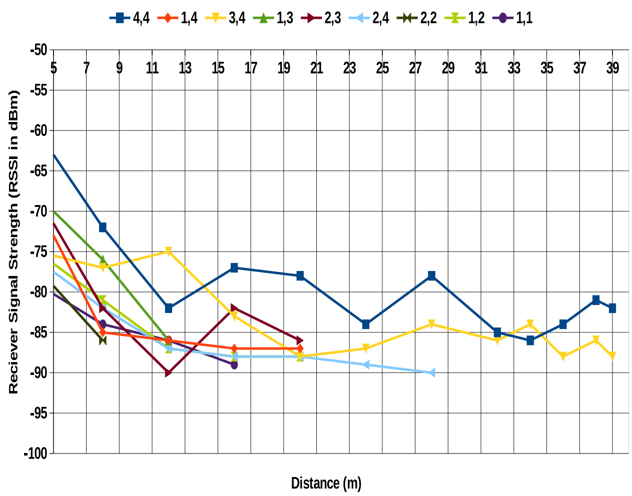


Figure 9. RSSI variations in Indoor (with obstacles) with respect to different power level combinations.

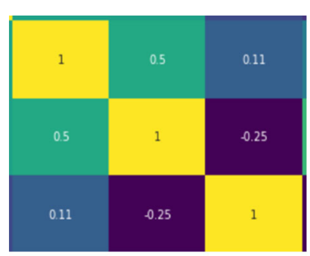
Plane ground, and indoor with obstacles, where the power level of one node is set as the highest and the other node set as the lowest. Both LQI and RSSI are decreasing towards the distance in all environments. The LQI values of CC2420 vary from 0 dBm (worst case) to 255 dBm (best case). Figure 4 shows the link quality change with distance in selected environments for successful communication. In our scenario, successful communication is defined as communication with a packet receiving rate above 98%. The LQI values show low variation in the outdoor plane ground since the radio connectivity is higher than in obstacle-prone environments. In the other two experimental areas, there is a drastic variation in LQI because of the instability in connectivity due to interference and signal scattering.

In the plane ground, quality communication is obtained up to a range of 100 m. The LQI and RSSI readings for that communication are 205 dBm and −83 dBm, respectively. But when it comes to obstacle-prone environments, the quality communication range is decreased to 20 m (indoor) and 25 m (outdoor) with an LQI of 200 dBm and RSSI of −87 dBm. This drastic range variation (with and without obstacles) is due to the interference and signal fading with obstacles and Wi-Fi signals. The communication protocol used in this study is IEEE 802.15.4. It is operated in the 2.4 GHz ISM band. The Wi-Fi standard also uses a 2.4 GHz ISM band. So the signal spectra of both the protocols will overlap, and this signal interference results in performance degradation during communication in Wi-Fi enabled environments. From the observations, it can be inferred that the permissible range of LQI for successful communication is 255 dBm to 195 dBm. Below these levels, the communication quality in terms of PRR degrades drastically. The investigations show that the acceptable range of RSSI is −60 dBm to −90 dBm for quality communication.

Figure 6 and figure 7 represent the relation between link quality and distance in different power level combinations. The RSSI to distance is plotted in figures 8 and 9. From the plots, it is clear that sender and receiver power levels influence the link quality and RSSI values of communication. For example, indoor communication of a distance up to 15 m is enough to set a minimum power level for the sender and receiver for quality communication. But outdoor, this minimum power combination can cover up to 20 m. Another inference from this experimental data is that if we wanted to change sender power dynamically, the power has to be set based on the receiver power since the LQI and RSSI rely on the transmission power-receiver power pair.

Figure 5 shows the variation of RSSI for receiver power and transmitter power pair indoors and outdoors. A combination of (4,1) and −69 dBm is obtained, whereas it becomes −75 dBm in the (4,3) combination. It is due to the influence of signal interference. In the majority of IoT applications [29], the nature of the data transferred is of sensor readings, which is very smaller in size. So based on our collected data, it is found that up to −90 dBm RSSI and 190 LQI, the data will be successfully transferred without packet loss. Hence −90 dBm, 190 is fixed as the threshold for quality communication. It is seen that there is a high correlation between the transmit power- receiver power (tp-rp) pair and LQI/RSSI. But this relation is not linear, as it fails to use conventional linear prediction approaches. Therefore, a classification approach is proposed to predict the desired power level.

From our empirical investigation, the inferences that can be drawn are as follows. In CC2420, for a good link, the RSSI value varies from −90 dBm to −60 dBm and LQI changes from 255 dBm to 190 dBm. In the majority of IoT applications [28], the nature of the data transferred is sensor readings, which are very smaller in size. So for such applications, the RSSI and LQI threshold can be set as



	coef	std err	t	P>|t|	[0.025	0.975]
const	7.3850	0.187	39.474	0.000	7.018	7.752
distance_in_mtr	0.0624	0.002	34.957	0.000	0.059	0.066
RecieverPower	0.3159	0.016	19.901	0.000	0.285	0.347
lq_a2b	8.412e-05	0.000	0.266	0.791	-0.001	0.001
rssi_rcvd	-0.0745	0.002	-33.500	0.000	-0.079	-0.070

Skew:	-0.369	Prob(JB):	1.50e-19
Kurtosis:	3.081	Cond. No.	3.40e+03

Figure 10. Linear Model fit - Summary.

Table 2. Class labels.

Class Label(y)	Transmission power
y_1	-3 dBm
y_2	2 dBm
y_3	8 dBm
y_4	10 dBm

Table 3. Comparison of considered models.

Algorithm	Accuracy	Model size	Prediction time (seconds)
Support Vector Machine	92%	87 KB	0.002
Naive Bayes	69%	973 bytes	0.002
K-Nearest Neighbour	99%	405 KB	0.001

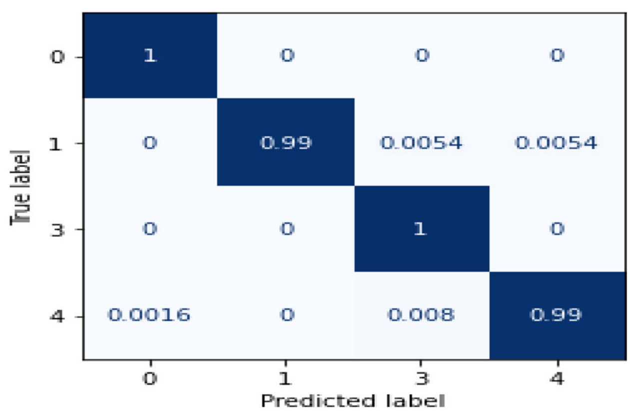


Figure 11. Confusion matrix for KNN.

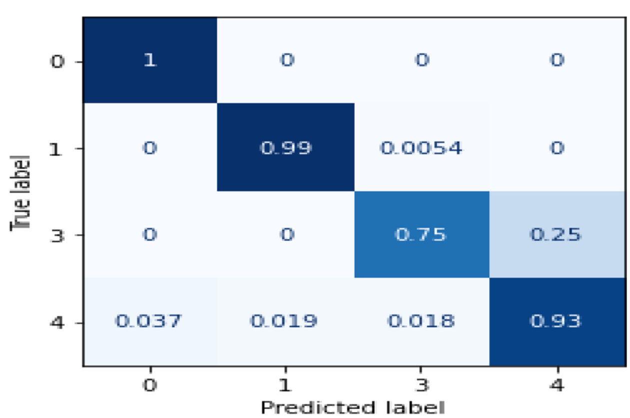


Figure 12. Confusion matrix for SVM.

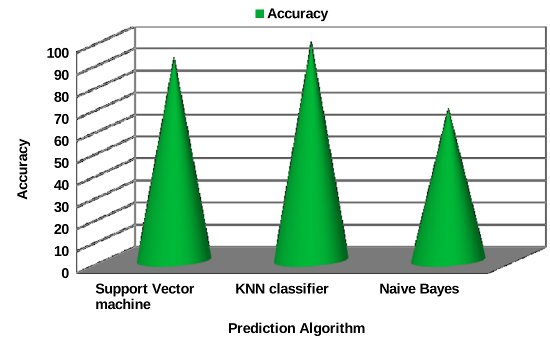


Figure 13. Comparison based on accuracy.

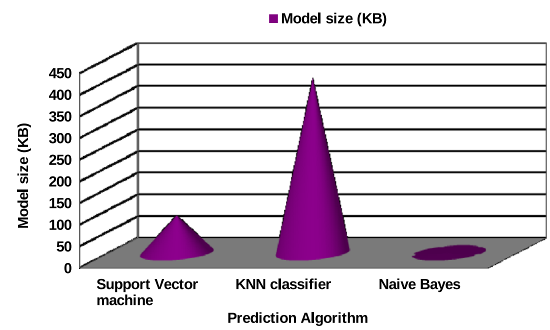


Figure 14. Comparison based on model size.

-90 dBm and 190 dBm. It is seen that there is a high correlation between the transmit power- receiver power (tp-rp) pair and LQI/RSSI. But this relation is not linear, as it fails to use conventional linear prediction approaches. Therefore, a classification approach is proposed to predict the desired power level. Since communication quality is influenced by distance and receiver power, these parameters are included as the input vectors in the proposed method.

4.2 *Transmission power modeling*

Depending on the results of the present investigation, a model is proposed for predicting transmission power levels. The objective of this prediction system is to give each node the capability to predict the optimal transmission power level needed for neighbour node communication with good link quality. This system also helps to dynamically change the sender transmission power level over time, to address environmental impact. The input vector for the prediction algorithm is read from the service messages, and the power level can be set during the network configuration. All the previous literature [24, 25] had considered a linear relationship between the parameters such as RSSI, LQI, and transmission power. Hence, they had modeled the transmission power prediction as to the linear combinations of these parameters. But in real environments, the reality is

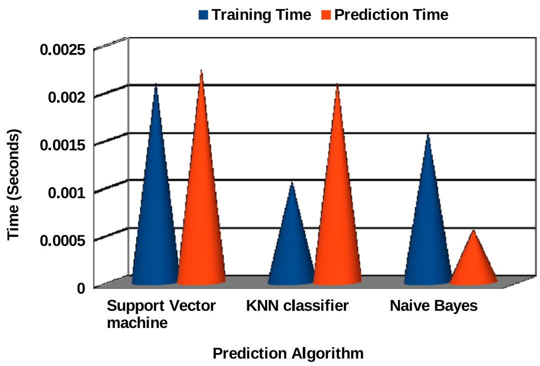


Figure 15. Comparison based on execution time.

different, and the linear relationship among these parameters is never obtained. The first trial is performed with the linear model, as most previous works were with linear assumptions. Multiple linear regression tries to find a linear relationship between multiple independent variables and a dependent variable [30].

$$Y = a + b_1X_1 + b_2X_2 + ... + b_nX_n + \varepsilon$$

Where Y is the output variable, X_i is the dependent variables, $i \in \{1, 2, 3, 4\}, \varepsilon$ is the residual. The model is evaluated against multicollinearity assumption and R-squared value. A heat map is plotted with the target variable and predictors. The results of the fit model are shown in figure 10. The fit summary shows that the R-Squared value is 0.441 and the condition number (cond.No) is 3.4e+3. These results show that the linear regression is not suitable for the data set built from the conducted experiment.

A different approach for predicting the transmission power is proposed in this work. Here, the power prediction is viewed as a classification problem since the power levels are discrete and finite. Therefore, each power level can be considered a different class. This proposed model has four different classes for four power levels [27], as shown in table 2. The data sample contains the features such as distance between the sender and receiver, link quality indicator, RSSI, and receiver power level.

The model is formulated as a four-class classification problem for transmission power prediction. Four target classes $Y_i, i \in \{1, 2, 3, 4\}$, are used here for modeling. A sample vector X_i consists of {distance from the receiver, receiver power, RSSI, LQI} of a single communication. The training is performed with 5231 samples. It is done at a machine with high computational power, and the model is generated. This model can be incorporated into the IoT device and used with any new vector for transmission power prediction.

Commonly preferred supervised learning algorithms in networking are k-nearest neighbour (KNN), Bayes classifier, and support vector machine (SVM) [31]. KNN is very simple to implement and is suited for fluctuating environments since all the work happens during prediction. So KNN is considered here. The model is analyzed with linear classifiers such as linear regression and Naive Bayes classifiers, and non-linear classifiers support vector machine with rbf kernel and KNN to choose the best power prediction model for accuracy, model size, and prediction speed.

The SVM classifier is designed to deal with binary classification. Further, it is extended to multi-class classifier [32]. The training set X is mapped to a higher dimensional plane in multi-class SVM. Here, the 4-dimensional feature and vector map to the 4-dimensional class vector.

$$f : R^4 \rightarrow R_s^4$$

A weight vector $[W_{i_j}]$ is constructed during training $i \in \{1, 2, 3, 4\}$ number of classes, $j \in \{1, 2, 3, 4\}$ number of feature vector.

$$\begin{aligned} f(X_i, W, b) &= WX_i + b \\ &= S \end{aligned}$$

Where b is a scalar vector.

S is the score vector.

The training set X is assigned to a class with a higher S value.

class of X= $argmax_{i=1....n}\left((W^n)^T f(X_i + b^n)\right)$.

Radial bias kernel function with $\gamma = 0.250$, is selected here.

$K(X_1, X_2) = exp(-\gamma \|X_1 - X_2\|^2)$

X_1, X_2 are two sample vectors.

The trained model is tested against testing data generated by splitting the data set in 70 and 30 ratio [33]. The model produced an accuracy score of 92%.

The basic concept behind the Naive Bayes classifier is the Bayes theorem. Four feature vectors used are: $X = \{X_1, X_2, X_3, X_4\} \in R^4$, target class $y_i \in Y, Y = PL_1, PL_2, PL_3, PL_4\}$, power levels.

Joint distribution function is $P_r(X, y)$, the learn function is $f(x) : R^4 \rightarrow y$. Bayes decision rule is to choose the class with the highest posterior probability.

$$\begin{aligned} f(x) &= argmax_y P_r(y/\vec{x}) \\ &= argmax_y P_r(\vec{x}/y)P(y)) \end{aligned}$$

The performance of this model is very poor in our data. An accuracy score of only 68.8% with the test set is obtained.

The KNN is based on similarity. It is measured in terms of the distance formula. Since the algorithm is non-parametric, it does not bother about the underlying data distributions. So it is better for real-time data since theoretical assumptions about data distribution fail in practical situations. For calculating similarity Euclidean distance $d(X, Y) = \sqrt{\frac{\sum_{i=1}^{m} (x_i - y_i)^2}{m}}$ is used here.The default K value of 1 is chosen for training. A high accuracy score of 99% is obtained with this model (table 3).

The models which produced above 90% accuracy score are SVM and KNN. The analysis based on the confusion matrix is also performed to get more insight. The confusion matrix is a tabular representation of classifier performance. It is a measure of true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Figures 11 and 12 show the confusion matrix generated by testing KNN and SVM models. The true labels shown 0, 1, 3, 4 represents the class label y_1, y_2, y_3, y_4 corresponding to each power level. In the KNN model, the lowest power and power level 3 are predicted with 100% accuracy. For power level 2, 0.0054 % wrongly predicted as power level 3, and 0.0054% wrongly predicted as power level 4. In the highest power level, 0.0016% wrongly predicted as the lowest power and 0.008 % power level 3. In SVM, Even though misprediction happened for power levels 2 and 3, it does not affect the communication quality since the predicted power levels are higher than the actual. But it causes power loss. While considering power level 4 (highest), all the wrongly predicted power levels are below the actual one. It causes packet loss. Based on the inferences made from this analysis, KNN is found to be better than SVM.

The performance comparison of the generated models based on model size and prediction time is also executed. Table III summarises the obtained results. This model has to be deployed in an IoT node. So it is relevant to consider the model's size and time taken for the prediction as of the performance metrics. The plot 14 and 15 show the comparison of the selected model based on model size, prediction time (for a single input vector), and training time. Naive Bayes performs better in model size and time-taken. Considering prediction accuracy in the plot 13 SVM and KNN perform better than Naive Bayes. But whenever the size of the training samples increases, the KNN model size and the prediction time increase since the model keeps all unique samples in ranking order. The SVM is better suited for this scenario, considering model size, accuracy and prediction time.

5. Conclusion

A real-time investigation is conducted to analyze the impact of transmission power on communication quality. The variation of link quality in different interference conditions is also explored in the paper. The work is contributed towards the power level prediction with a classification problem. A data set is created from the real-time experiments and used for power modeling. The parameters such as receiver power, transmit power, RSSI, LQI, and communication distance are considered in the present work to model the transmit power. Hence, the predicted power level maintains the quality of service parameters of wireless communication. The proposed prediction system can be installed in IoT nodes and used as the routing parameter for the neighbour node selection process. The present work can be extended by installing dynamic power level prediction in network layer routing, and further investigations can be conducted to analyze communication quality.

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