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Enhanced Routing for Low Power and Lossy Network Based on Link Quality Estimation

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Abstract: Internet of Things (IoT) network is designed using a set of wireless sensor nodes connected together through a Base station. The sensor nodes capture the data about the surrounding environment and forward it to the base station (BS) along with the geotag and timestamp. For a better quality of service in a IoT network the intelligent routing becomes essential factor. The routing protocol must be energy efficient to prevent packet loss or packet drop, and early dying of certain nodes. Hence it also becomes necessary to balance the energy spending in the network by implementing optimal routing decisions derived from intelligent machine learning techniques. Many researchers have provided solutions for energy efficient routing in IoT network. However the solutions provided need to be enhanced or redesigned to address other challenges and issues in an IoT network. This paper proposes a link quality estimation mechanism when a node is considering it neighboring node as a parent node. Based upon the experiments conducted in this research by implementing the proposed routing protocol it is observed that the routing algorithm exhibits better performance with respect to the following performance metrics including average energy consumption, packet drop rate, overall network life time, and average end to end delay.

Keywords: IoT, Energy efficient, Machine Learning, Link quality estimation, Energy consumption

I. INTRODUCTION

Internet of Things (IoT) provides a new computing environment which encompasses the features of wireless sensor networks, devices, and software. IoT provides a platform to connect the devices installed across the globe through cloud network for a coordinated task [1]. The IoT architecture has to provide solutions to challenges and issues caused due to interconnection of devices to communicate among themselves. The routing protocols commonly used for wired, wireless (MANET / Sensor) networks can be utilized as such for a Low-Power and Lossy Networks (LLNs) [2]. The IoT network consists of heterogeneous devices ranging from a micro/mini device to a large house security device. The routing protocols must have intelligence to make effective decisions on optimal routing under challenging scenarios. The topology of the connectivity in the IoT network provides scope for mobility of the IoT devices and under such circumstances the intelligent routing algorithm can able to manage the mobility of the nodes and can possible route data in an energy aware intelligent route. IPv6 is used for routing data in the IoT environment. But the data gathering, representation, storage and communication must be synchronized for better performance of the IoT application [3]. The machine learning based strategies will help to achieve intelligent data collection and communication.

Wireless Sensor Network (WSN) is a main part of the IoT architecture which is strongly influencing the networking and IoT research groups globally [4]. The advancements made in the field of Micro Electro Mechanical Systems helped in the development of changes in the smart IoT sensors and devices. The sensor nodes sense the surrounding environments, accumulate, and forward the data. In such environment the energy dissipated by the sensor node for its operations needs to be efficiently controlled. The sensor nodes are equipped with a irreplaceable power sources mostly a battery with limited power and bandwidth available for communication [5]. Hence it becomes the essential task to design the nodes of the network to be energy efficient and the routing protocols must be designed to improve the QoS in the network. Clustering of the sensor nodes is one of the most widely used and successful technique for reducing the energy consumption in the network. Hierarchical routing is adopted in the network where nodes are clustered into groups with a cluster head (CH) node. Hierarchically clustered network becomes scalable and energy efficient [6].

In a hierarchical routing the routing of data from the sensor nodes to the base station through the cluster heads involves two steps namely Cluster Head selection and forwarding of data packets from CHs to BS. The cluster heads are changed once after a pre-defined period of time enabling them to live long in the network. Apart from power there are other challenges to be faced in designing a network topology and protocol for an IoT network. In a conventional wireless network the topology of the designed before constructing the network. In a deterministic deployment of nodes in a network the data can be transferred in a predetermined path. But if the nodes are deployed randomly routing decisions are to be taken in an ad hoc fashion as there is no prior knowledge of network topology. In a dynamic network the routing paths have to be changed quickly to match the mobility of the nodes in the network [7]. In this type of networks packet drops will be high as the nodes change their position dynamically.

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The network layer in IoT device can be divided in to two sub-layers; routing layer which manages the transfer of packets from sending node to destination node and encapsulation layer which encapsulates the packets [8]. The most commonly used routing protocol is Routing Protocol for Low-Power and Lossy Networks (RPL).
RPL is a distance vector based protocol which supports multiple data link protocols including IEEE 802.15.4, IEEE 802.11 AH, Bluetooth Low Energy, ZigBee smart energy, G.9959, and LoRaWAN [9]. Initially a DAG is built which has only one path connecting the leaf node to the root. All the packets from the leaf node to the root node flow in the same path. Initially each node in the network broadcasts an information object to advertise them as the root node. When the message is being propagated in the network the a directed acyclic graph (DAG) is built and when a leaf node wants to send data packet to a destination it sends a destination advertisement object to the parent node and the parent forwards it to the root node. After receiving the destination advertisement object the root node decides where to forward the data packets sent by the respective leaf node depending the distance from the leaf node to the destination node. The process of constructing the directed acyclic graph in IoT network is presented in Fig. 1.

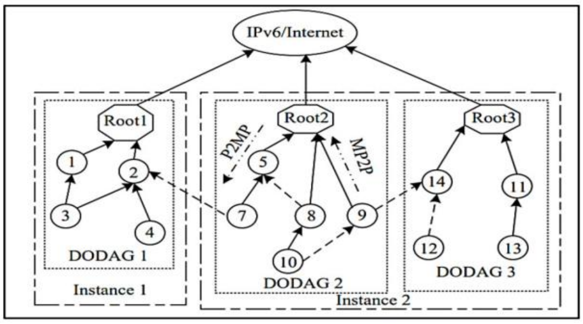

Fig.1. Splitting of network and construction of DODAG

When a new node wants to join the network it sends a request to the root node and in response to the request the root node sends an acknowledgement message denoting the acceptance to join the network. The meta-information about the DAG is available only with the root node. The RPL protocol can be stateless or stateful depending upon the nature of the communication carried out within the network as shown in Fig.2. In a stateless approach the intermediate nodes stores the details of their parent node only whereas in a stateful approach the intermediate nodes keep track of both the child and parent nodes. The communication within the network will not involve the root node.

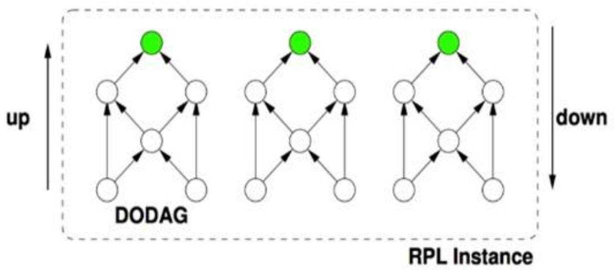

Fig.2 RL Topology

For building a new instance the root node issues a message regarding the directed acyclic graph (DAG). The information available in the message includes a DODAGID, rank value of the nodes, and objective code point (OCP). The rank of the child will be greater than the rank of the parent node. After receiving the message each node chooses the most preferred parent node and forwards the message to other nodes in a multicast manner. The DIO message mechanism in RPL as shown in Fig.3.

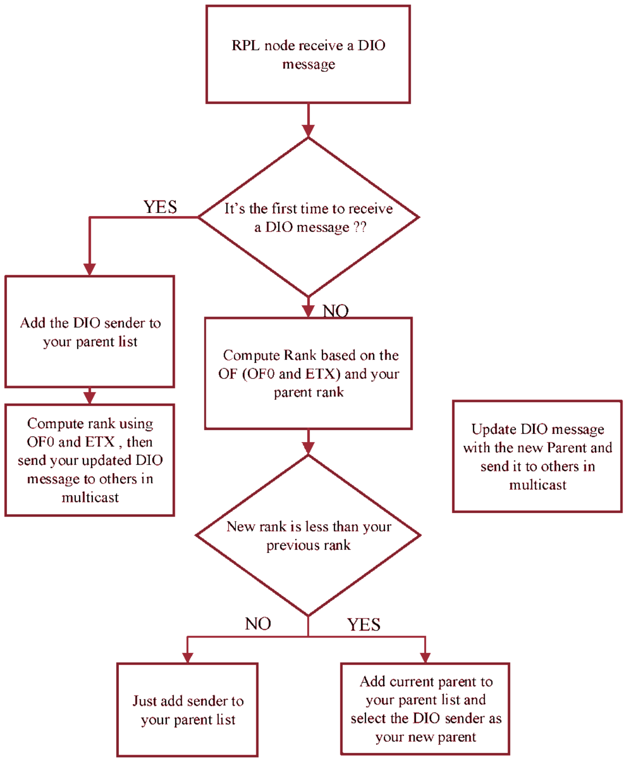

Fig.3. DIO message mechanism in RPL

The objective function can be used to define metrics to aid RPL nodes for translation of the metrics in to ranks. Rank is calculated using the objective function and it depends on certain routing metrics such as link quality, packet delay, and the connectivity in the network [10]. The rank can be expressed as the distance between the root node and the respective node. Based on the hop count objective function the rank can be calculated as

$$R(n) - R(P) + (default\ rank\ increase\ for\ minimum\ hops)$$

Where R(n) is the rank of the intermediate node in the DAG and R(p) is the rank of the respective parent node chosen by the node. The node chooses the parent node with rank represented R(P) which minimizes the R(n).

Expected Transmission Count (ETX) is defined as the minimum number of transmissions which are essential for transferring a data packet from one node to another over link [11]. The path ETX can be estimated by adding ETX of all the links along the path. When ETX is used for selecting the parent then each node selects the node with low ETX value as its parent. ETX over a link can be expressed mathematically as

$$ETX = \frac{1}{DF.DR}$$

Where DF denotes the probability that a neighbor node will send a packet and DR denotes the probability that the acknowledgement reaches the neighbor node successfully. The rank of a node can be calculated based on the following mathematical equation

$$R(n) = ETX + R(P)$$

Where R(P) denotes the rank of the parent node. The rank of a node can be defined as the sum of its parent rank and ETX of the path.

This paper attempts to enhance the routing with RPL protocol using a link quality estimation approach. The rest of the paper if organized as follows. The section 2 presents review of the related works and the section 3 gives an overview of the link quality estimation methods. The section 4 presents the proposed methodology and the section 5 includes the experiments and the results with a clear analysis. Finally the section 6 concludes the paper with a scope for future work.

II. RELATED WORK

WSN provides a platform for low cost deployment of IoT devices and the data communication is carried out in a multi-hop fashion. The multi-hop communication must be efficient and reliable to support the IoT application. The main focus should be on minimizing the resource consumption in the network. This is more essential for a low-power and lossy IoT network where frequent link failures are observed due to the mobility of the IoT devices. In this kind of network scenarios selecting an optimal routing path is essential and it is challenging also. Overhead due to collection and processing of link quality information for optimal route selection makes it difficult to limit the power consumption effectively. After much effort from various research communities a standardized version of RPL protocol was released to have a common routing protocol for IP based WSNs. RPL aims at constructing a multi hop mesh topology utilizing a set of lossy links between the nodes [13]. RPL is a gradient based routing algorithm and many performance studies revealed that it has reliability issues. The algorithm does not have the ability to respond dynamically to the changes in the network due to node mobility or other factors including channel interference, multi-hop issues, and mismatching radio patterns among the nodes [14]. Many variants of the RPL algorithm have been proposed in various literatures for optimizing the route selection, discovering efficient route and managing the topology of the network. For maintaining the historical and current information regarding the link quality and the routing paths, utilization of tweaking routing procedure was also not effective [15].

In general a highly efficient, accurate and dynamic link quality estimation procedure is essential as part of routing protocol for selecting the optimal route from source to destination in a time varying network scenario. It is a common fact that the overall network throughput will be high and the packet loss will be low when the data packets are transferred over high quality network links. The less packet drop reduces the number of re-transmissions. As discussed earlier in the previous section the link quality estimation is essential for managing the stability of the network and for analyzing the dynamic behavior of the links. Using the estimations the short term variations of the link quality can also be predicted well in advance to take necessary counter measures. Broadcast based probing is generally used for link quality estimation. But RPL uses Trickle algorithm to control the broadcasting of route control messages and hence the implementation of broadcast based probing is complex [16]. Depending on the number of neighbors and frequency of probing the overhead involved in broadcast based probing will increase linearly [17]. The routing overhead introduces congestion in the network. In other hands the less frequent probing will make the estimation inaccurate and limits the routing ability to match the dynamics of the link in real time. Few solutions have been proposed for adaptive link quality estimation for minimizing the probing overhead [18]. But these solutions cannot be adopted for a lossy and low power networks as they require large tables to maintain the link state.

Another popular routing protocol used for under water communication is Channel Aware Routing Protocol (CARP) [12]. It is distributed in nature and can be used for IoT application because of its light weight packet formats. The packets are forwarded through a path based on the quality of the link estimated. The quality of the link is estimated using the past historical data transmission collected from the neighboring nodes. The protocol has two stages; network initialization and data forwarding. During network initialization a broadcast hello packet is floated from the receiving node to all the other nodes in the network. During packet forwarding phase the data packets are routed from sensor to receiving node dynamically in a multi-hop fashion. Some variants of the CARP routing algorithms are proposed in various literatures to reduce the communication overhead in the network.

In some of the variants of RPL, for path computation content based approach is adopted by which the network is split virtually in to numerous instances. Each instance handles their data transfers independently depending on their objective function. To avoid cyclic paths in the logical topology of the network the rank of the intermediate nodes must be lowered when approaching towards the DODAG root [19].

III. LINK QUALITY ESTIMATION

Estimation of the link quality in a wireless network with lossy and mobile nodes is more challenging and therefore it becomes essential duty of the designers to take an account of the low power link characteristics of the nodes in the network. The characteristics of the low power network links can be analyzed using the following metrics:-

PRR (Packet Reception Ratio) –also referred as packet Delivery ratio which is the ratio between the number of packet sent from the sender to the number of packets received successfully by the destination node and Packet Error Ratio can be computed using (1-PRR). RSSI (Received Signal Strength Indicator) which is maintained in an RSI register which holds the signal strength of the received packets. The register holds the noise floor when there is no transmission. Signal to Noise ratio is another metric which is the difference between the received signal strength of the signal with and without noise.

LQI termed as Link Quality Indicator is introduced in IEEE 802.15 standard which is measured based on the first 8 bits present in the received packet.
The link quality estimation is carried out in three steps: link monitoring, link measurements, and evaluation of the metrics which is described in Fig.4.

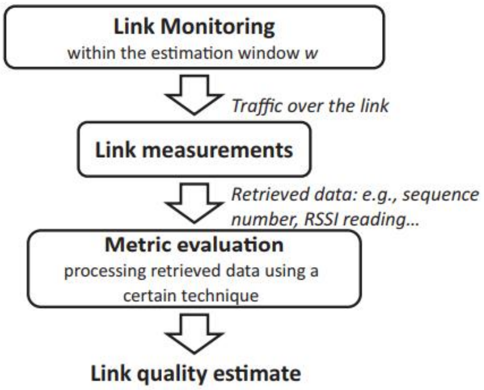

Fig.4. Processes involved in link quality estimation.

The Link Quality Estimation needs certain link measurements such as the packet sequence number of the every received packet. Link monitoring will involve the strategies to observe and collect statistics regarding the links connecting the node over a period of time. The information collected including the timestamp, Received Signal Strength, sequence numbers are used estimate the receiver side link quality estimators. Based on these extracted information a metric representing the link quality is calculated using techniques including regression, fuzzy and filtering. In a WSN the energy spending should be conserved more and hence the link quality estimation should consume less energy and communication overhead. Also link monitoring with high beaconing will require more energy and it should be avoided for utilization in WSN. In routing protocols which depends on link quality estimation for routing, fault tolerance, and mobility management the validation of estimated link quality value itself is challenging. In RPL routing protocol the support for the network with mobile nodes is not adequate and hence efforts are taken to ensure the mobile devices are made to remain connected to improve the overall performance of the network. Some of the works focused on predicting the stability and quality of the links connecting the mobile nodes. Some of the approaches focused on utilizing enhanced hand-off techniques and local repair procedure to manage the mobility in the network.
During DODAG selection the nodes should adopt a mechanism to filter out candidate parent whose availability is fluctuating and consider only stable choices. When a node is considering its neighbor node as a parent then it should verify the bidirectional connectivity and the quality of the link connecting them.

IV. PROPOSED LINK QUALITY ESTIMATION METHOD

This paper proposes a data driven approach for link quality estimation. The initial task is to prepare the dataset of traces for building the link quality estimation model. The dataset consists of a time series value of packet sequence number and the respective RSSI value. The RSSI value can be obtained from the hardware registers of the transceivers. To get the packet transmission level metrics including PRR, and PSR can be calculated using a mathematical procedure. The dataset has considerable amount of missing and invalid data values. These invalid and missing values have to be preprocessed before proceeding with the modeling process. The missing values are handled using a Gaussian based interpolation method by which the missing values are replaced by a random value chosen with respect to the immediate previous and next valid values. The RSSI values are integer which ranges between 0 and 127. This paper adopts a supervised methodology for classifying the quality of a link in to any one of the following three categories namely bad, intermediate, and good.

The dataset contains the raw RSSI value and the respective sequence number and the label is generated as per the following mathematical expression:

$$y = f(PRR) = \begin{cases} good, & if\ PRR \geq 0.9 \\ bad, & if\ PRR < 0.1 \\ intermediate, & otherwise \end{cases}$$

$$y = [y1, y2, y3, \ldots\ldots, y_n], \forall y \in \{good, bad, intermediate\}$$

The link quality estimation process should be simple and less complex but in most of the approach mentioned in the literature it is highly complex and requires more computational power which is not feasible in a LLN. To make the link quality estimation more accurate, new features are generated from the existing RAW RSSI values given in the dataset. The standard deviation and average of RSSI values with in a time bound is estimated and the combine feature values of RSSI, RSSIstd, and RSSIavg are used to classify a link as either good, bad, or intermediate. In a classification problem using a prior knowledge of the problem, a new instance can be classified using a Bayes classification procedure. The given dataset is a collection of correctly classified samples and a simple probabilistic classification procedure based on Bayes theorem. It works based on assumption of conditional independence between the features and the class variable. For a given feature instance X (x1……xn) and the class variable y then as per the Bayes theorem the relationship can be expressed mathematically as

$$P(y \mid x_1, \ldots\ldots x_n) = \frac{P(y)P(x_1, \ldots\ldots x_n \mid y)}{P(x_1, \ldots\ldots x_n)}$$

Gaussian Naïve Bayes algorithm for classification is employed in this work which assumes the likelihood of the features as Gaussian distribution and the probability of x_i for a given y can be expressed mathematically as given below:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma^2 y}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma^2 y}\right)$$

V. EXPERIMENT AND RESULTS

In majority of the research contributions for estimation of link quality using machine learning algorithms nonlinear models including neural network, Support Vector Machine with nonlinear kernels and decision trees where each of the model has several limitations and computational power requirement. The naïve bayes classifier is considered since there are less number of features when compare to the more number of samples.

When neural networks are employed and when the network is rebuilt with some heterogeneous nodes then the model has to be completely retrained. With these limitations and disadvantages of non-linear models, a simple probabilistic model is preferred. The dataset is contains unbalanced trace sets and re-sampling strategy is employed to over sample the instances.

The Random Over Sampling (ROS) approach equalized the ratio of different classes of traces available in the dataset. The over sampling is carried by reusing the traces belonging to minority classes and the process results in a larger re-sampled trace set. The simulation of the LLN with a RPL and UDP communication is implemented with COOJA simulation tool. The Table 1 presents the details of the simulation environment.

Table 1. Simulation Environment in COOJA

Parameters	Value
Objective Function	OF0
No. of Motes	30
Area of Network	1000 Sq.Mtr
Topology	Random
Simulation Time	15 mins
Wireless Channel	UDGM
Tx Range	100m

The COOJA simulation generates pcap files which contain the traffic details and these pcap files are analyzed to extract more information regarding the network, links connecting the nodes, and the packets transferred between sender and receiver. The main metrics used to measure the RPL performance with OF0 objective function are Control Traffic Overhead, Expected Transmission Count, Latency, and Energy Consumption. The control traffic overhead represents the number of DIO, DAO, and DIS messages transferred from the client nodes to the root node. The power consumption helps to estimate the lifetime of the LLN. The packet delivery ratio measures the total received packet at the root when compared to the total packets sent from the client nodes.

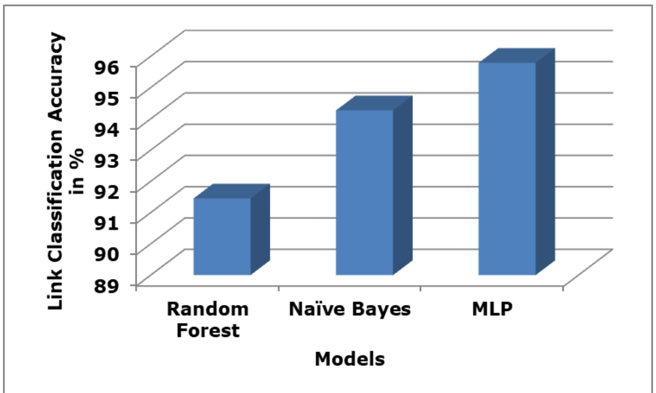

Fig. 5 Comparison of Model Accuracy

For training the model synthetic features are generated such as average and standard deviation of RSSI over a time window. A combination of RSSI (raw), $RSSI_{avg}$, $RSSI_{std}$ proved to be yielding better results. The changes are incorporated in the COOJA simulator and both conventional RPL and modified RPL was simulated. The comparison of the results of the both the simulations proved that RPL with proposed link quality estimation exhibited higher PRR with less latency. The link quality classification was analysed using three machine learning models including random forest, multilayer perceptron and naïve bayes classifiers. The Fig. 5 presents the accuracy of the different classifiers used.

Eventhough the accuracy of the MLP model was slightly higher than the Naïve Bayes model the individual class level accuracy for good and bad links are higher for Naïve bayes model. As it is a probabilistic based model the classification of intermediate links are not accuracte upto the level of MLP. It misclassifies the intermediate links as either good or bad category incorrectly.

The Fig. 6(a)-6(c) shows the plot of the confusion matrix of the best models chosen from k-fold cross validation process. The stratified cross validation utilized during training ensures that the same proportion of different class was used in training the model.

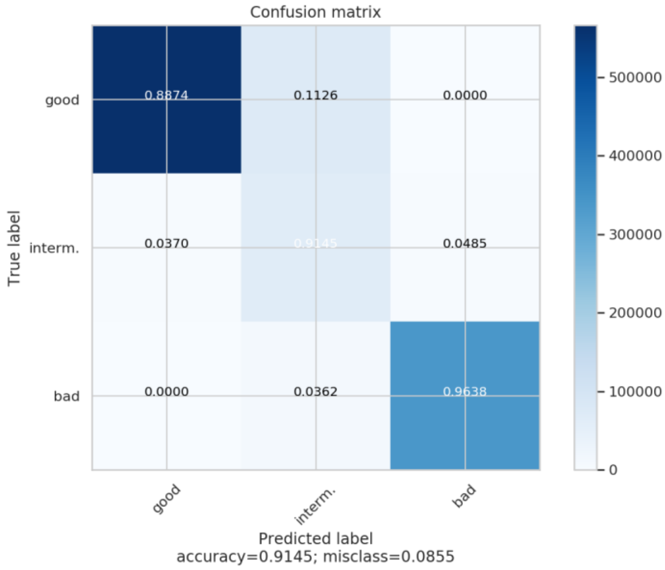

Fig. 6.(a) Multi-Layer Perceptron

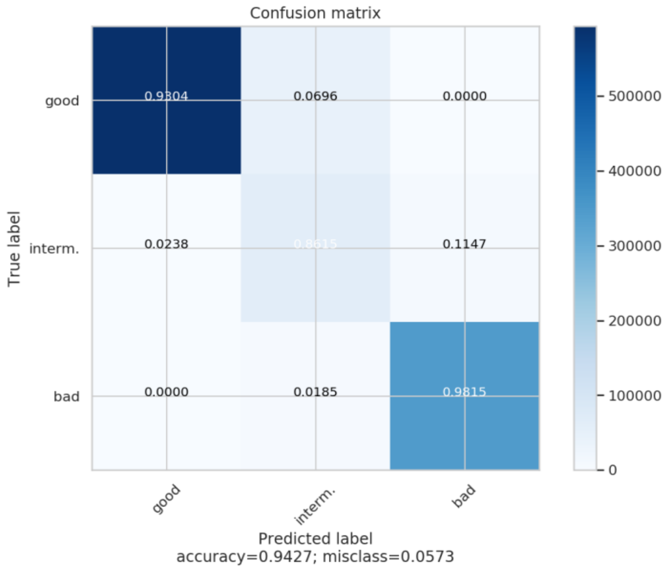

Fig. 6. (b) Multi-Layer Perceptron

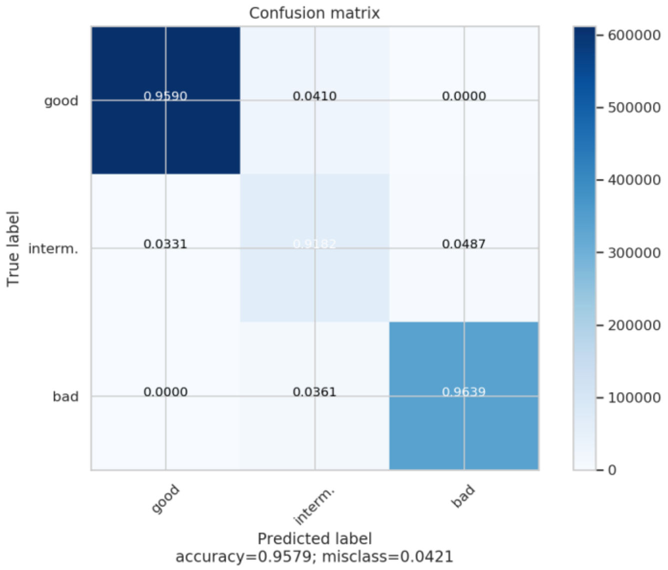

Fig. 6.(c) Multi-Layer Perceptron

VI. CONCLUSION

In many of the literatures the hardware metrics are used for estimating the quality of the links including the RSSI, LQI, and SNR. This paper focused on proposing a methodology for estimating the quality of the link based on the RSSI and other derived parameters from the RSSI. The design of a link quality estimation algorithm is crucial and challenging task in IoT routing. The link quality estimation can be helpful in designing an optimal handoff technique to support the mobility of the sensing nodes in IoT network. The proposed method utilizes a data extracted from the retrieved packets including the sequence number and RSSI for estimating the link quality at the receiver side. The experiment included the following sequence of tasks interpolation for handling the missing values, feature engineering, over sampling the dataset and constructing the machine learning model. Based on the comparison of the results mentioned in the literature and experiments conducted, it is obvious that proposed approach performed better when classifying link quality for the selected representative dataset than algorithms mentioned in literatures. The overall results proved that link quality estimation based on the data traffic proved to be more accurate than the beacon traffic based approach.

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