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Performance Analysis of Long-Short Memory Prediction of Device to Device Communication in LORA Based Network

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A B S T R A C T

Device to Device (D2D) communication has been on the research focus for a while as its prevalence in 5G and the incoming 6G could aid communication between two user equipment without the need for the base station in a cellular network. The effect of this is the reduction of pressure on the cellular network increasing the quality of service (QOS) as long as both devices communicating are in radio range while using radio technologies other than the cellular network. However, this promising technology can be considered less effective for mobile devices as they can move out of radio range, making it compulsory to switch back to the cellular network using the base station to relay the communication between them. Thus, resulting to the increased pressure on the communication network and reduced QOS. This switch in link can be avoided in some D2D communication that still requires human control by forecasting the dynamic Received Signal Strength Indicator (RSSI) which varies with respect to the distance between the devices. This forecast can aid prompt control decision to ensure that the devices are in communication range. This work therefore presents Long-Short Memory Prediction of Device to Device Communication in Lora Based Network to predict the future strength of the path of a LoRa based D2D network. This was achieved by simulating two devices 100m apart moving towards and apart from each other. The RSSI, the path loss and the distance between the nodes were logged. The RSSI was subdivided into train and test data. The train data was used to train an LSTM model and forecast was made using same model. It was observed that the forecast was following the same trend with the test data with RMSE of 4.848, 5.153 for each node when moving towards each other and RMSE of 4.68 and 4.17 when moving apart.

Keywords: Device to device communication, Long-short memory, LORA network, Received signal strength indicator

1. Introduction

Device to device (D2D) communication is a paradigm used to describe the technology that aids the communication between two or more UE's with little or no use of the Base Station (BS) (Ziadi & Asvadi, 2022).In other words, the aim of this technology is to ensure the connectivity between two or more UE's directly especially when it is a short distance communication that does not require much of the limited frequency spectrum (Hailemariam et al., 2019).This implies that the use of this technology will help to reduce the pressure on the network. This paradigm will improve the capacity of the future network such as 5G and 6Gnetworks.With its wide application in areas such as Vehicle to Vehicle (V2V) communication, IoT network extension, Machine to Machine communication, Content distribution, Location awareness Social Networking and e-Health. D2Dis a novel feature for Long Term Evolution 5G network and will aid offloading of mobile cellular network resulting to increased capacity and efficiency.

Generally, challenges in D2D include device discovery, spectrum resource allocation, interference management, power control and management and communication security. Among all these, device discovery is more important for D2D communication. This is because continuous communication comes after device discovery. For effective device discovery, the important data needed includes device location, channel quality and device identity. Getting this data, requires various techniques which can be classified based on Network influence in device discovery process and based on method of communication used in device discovery.

Device discovery based on network influence involves the use of network functionality to locate the device intended for communication. This kind of device discovery is called Network Assisted Discovery. This, sometimes, could involve the use of the BS to aid device location identity (Rahim et al., 2020). This technique which could mitigate collision (Ziadi & Asvadi, 2022) estimates the proximity or to locate devices in D2D network(Li & Tsai, 2018).Aside the use of network assisted device discovery, Rahim et al., (2020), highlighted the device discovery in which the base station is not involved. This kind of device discovery involves devices only. This is called distributed device discovery.

Distributed device discovery generally could be based on communication methods. One method involves the transmitting device sending broadcast randomly or receive a broadcast randomly at regular time intervals to discover devices within reach. This kind of distributed device discovery is called Randomized device discovery (Hayat et al., 2020). While another method could involve the transmission of beacon signal to a predetermined or a target device or the reception of beacon signal from a target device (Hayat et al., 2020). This type of distributed device discovery which is not random in nature is called deterministic device discovery.

Succeeding the process of device discovery is device to device communication so as to aid the exchange of data. According to (Kar & Sanyal, 2017), communication in D2D could be on licensed or unlicensed spectrum. The licensed spectrum which is also called known as in-band D2D communication (Kar & Sanyal, 2017) involves the use of channels paid for. This however involves the use of the BS. This kind of communication is often discouraged except when needed for network expansion. Instead of it, the use of unlicensed spectrum which is also known as out-band D2D communication is highly encouraged so as to offload the cellular network. With this, the capacity of the network is increased. To achieve this, technologies like Bluetooth (BT), WI-FI direct, and LTE which operates within 2.4GHz ISM band or 3.8GHz mm wave spectrum has been used. According to Kar & Sanyal, (2017), BT which is characterized with data rate of 50mbps and range of 240m, WI-FI direct, having data rate of 250mbps and a range of 200m and LTE with data rate of 13.5mbps and range of 500m are suitable for low data rate communication characterized with short range. Therefore, they are suitable for D2D communication. This however is limited as the energy consumed during operation is often high and is not suitable for long range communication. To combat this limitation, the Long Range (LoRa) radio technology was introduced (Moons et al., 2021). This technology which operates at low data rate, long range and low power is more suitable for D2D communication. Therefore, LoRa based network is considered in this paper.

2. Theoretical Concept

2.1 Device to device network topology

A D2D network is a network of devices characterized by short distances communication. In such network, the devices communicate with one another without the need for a cellular base station. This is done to ensure that the base station is offloaded so as to increase the efficiency of the cellular network. However, it is important to note that the state of the channel is important to either aid effective communication or to impede effective communication between devices (Rattaro and Larroca, 2020). In other words, the quality of the channel is important for good quality of service for effective D2D communication (Nauman et al., 2021).

Generally, D2D communication, a technology that is envisioned to aid the robustness of future communication could assume different network topologies. The reason for this is that the topology could be highly dependent on the application of the D2D communication. Some D2D application has static topology as shown in Fig. 1. This is because the D2D UE or nodes are not moving. This kind of application is mostly used in infrastructure such as in hospital. Where the laboratory communicates with the blood bank section and the doctors are in contact with the wards. All units send report to the central administrative block. The topology of this can be defined and static. In other words, the link device used for connectivity does not change position in the network. The advantage of such D2D network is that the quality of the channel used in communication is not affected by parameters like distance since the distance remains constant. Another application that uses this kind of D2D communication is the smart grid.

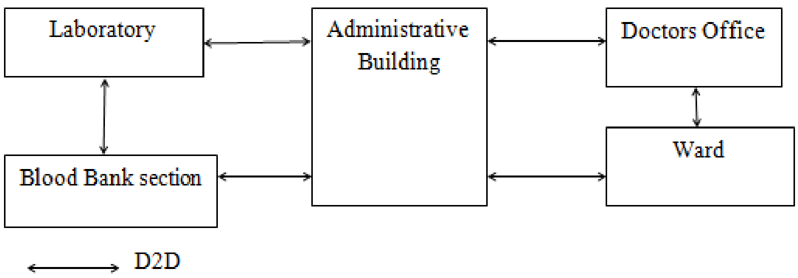


Fig. 1 – D2D communication in a hospital

Aside the application earlier stated, some other D2D application could involve mobile devices as shown in Fig. 1. Applications such as public safety services used for disaster management, vehicle to vehicle network and other mobile devices make the topology of this kind of D2D communication dynamic. This means that the structure of the network cannot be pre-determined. Furthermore, the quality of the link for communication varies in strength because the mobility of the UE. The limitation of this kind of application is that its dynamism in parameters such as distance between UE's also brings about variation in signal strength. However, to avoid loss of communication, sometimes the communication has to be rerouted through relays or rerouted through the BS which adds pressure and reduces the useful limited spectrum on the cellular network. Applications of D2D are illustrated in Fig. 2.

Fig. 2 – Application of D2D including mobile UE's (Umrao et al., 2016)

Lastly, there are applications which could be dynamic but could involve some level of control (Ioannou et al., 2022). This kind of D2D network application is seen in the control of drones or other forms of robots as shown in Fig. 3. Most times, one of the UE's like the downlink user equipment in this case, may be static while the upper link UE (the drone) is mobile. The drone may be a surveillance drone where the D2D communication is used for control of the drone and to receive video feeds of surveillance. As the drone moves away from the downlink UE, the channel used for D2D communication becomes less stable. This is evident in parameters such as Received Signal Strength Indicator (RSSI) among others which vary in magnitude. At points where the link is no more credible for communication, the base station can be used for relaying data automatically (Ioannou et al., 2022). This however, adds to the problem of cellular network overload which this research discourages. To avoid a handover it is assumed that a fore knowledge based on a forecast on whether the mobile device will be within or without radius of coverage is needed to aid adequate control so as to avoid a hand over. To achieve this, channel assessment is needed.

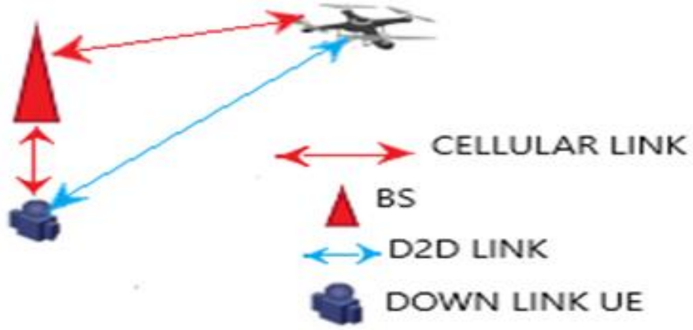


Fig. 2 – Application of D2D in drone control

2.2 Long short term memory and application in D2D Lora based network

Long Short Term Memory (LSTM) is Machine learning based algorithm that has recurrent neural network characteristics which makes use of previous time step data to make future predictions. Created to correct the weaknesses of the traditional Recurrent Neural Network which could access 10 past data at a time and forego others either because they varnish or explode, LSTM recurrent neural network has the ability to look at over 1000 previous time step data to make prediction. In other words it has the ability to remember information for prolong period of time (Le et al., 2019). The neural network which consists three control gates such as input gate, output gate and forget gate has the ability to read data sequentially as vectors$s = \{s_1, s_2, s_3 \ldots, s_t \ldots.\}$ where $s_t \in \mathbb{k}^x$represents vector readings of x having x dimensions at time t. In a nut shell, LSTM functions effectively with series data(Yu et al., 2019). It is also important to note that the gates help it to store relevant information and forget irrelevant ones during its operation. Another advantage of using LSTM over the traditional RNN is that if the Gap between data point is large, the prediction of RNN is prone to errors while LSTM is less erroneous(Yu et al., 2019). Furthermore, LSTM can be used for data with long term dependencies compared to other methods.

Generally, LSTM network can be categorized into LSTM dominated network or LSTM integrated networks (Yu et al., 2019). The former consist of basically LSTM networks of different architecture while the later consist of LSTM hybridized with other form of AI architecture. An example is the integration of LSTM with convolution neural Network (CNN)(Yu et al., 2019).

In evaluating the performance of the model, Nash–Sutcliffe efficiency (NSE) and Root Mean Square Error (RMSE) are popular NSE is used to evaluate the ability to predict variable different from the mean and gives the proportion of initial variance accounted for by the model (Le et al., 2019). While the RMSE measures how close is the predicted to the observed (Le et al., 2019).

LSTM has been applied to solve various problems in D2D network. One of such solutions is presented by authors in (Zhang et al., 2020) with focus on complete content path prediction in a D2D network via the use of LSTM. This was done to aid the reduction of congestion in the network. Similarly, in the quest to expand data transmission which aids the reduction of cell data and repeated cell data transmission, authors in (Xu, 2019)presented a D2D diffusion path prediction using LSTM.

In the bid to guarantee power efficiency in D2D network, authors in (Hu et al., 2019) used an Unmanned Area Vehicle UAV as temporary base station. Furthermore, the UAV was also used as a cooperative jammer to impede eavesdropping. To achieve success, LSTM based algorithm was used in the classification of potential pair of transmitters. The concept was to predict the available energy in the base station, the mobile state of the potential D2D transmitter to achieve optimal security performance in terms of D2D communication.

For the sake of power management in the base station of a D2D network, authors in(Jang et al., 2020) presented a technique to turn on and turn off the base station based on available user. To achieve this, LSTM was used to predict user traffic in multiple user time slots.

All this varying solutions is not what is considered in this research. The focus of this research is to predict link availability. To achieve this, varying parameters like the Received Signal Strength (RSS) due to the dynamism in the distance of communication in a D2D network is considered. For better communication, it is expected that the RSSI is good enough at any distance to sustain the communication. Considering the dynamism of the network due to mobile devices, it is important to data-log the RSS to be able to make predictions whether the two devices communicating are moving out of communication range. To achieve this, LSTM is deployed. The data generated at a regular time stamp is fed into the algorithm and to be able to predict the next sequence. With this applied to drone controls, it will be possible to ensure that the life of the D2D is sustained.

2.3 LoRa based network and characteristics

The need for wireless communication for day to day activity is to attain a level of smartness in the execution of processes and decision making. In other words, for smart technology to be deployed, an integration of sensors and wireless communication module is necessary. This helps to harvest information of events of interest remotely. Aside this, the harvested information which could be large is stored in a central location for example the cloud which could be limitless in capacity. With this advantage, such technology has been used in the remote detection of forest fire (Lora et al., 2019), emergency health communication system (Sciullo et al., 2018), Unmanned Area Vehicle (UAV) (Hazwan et al., 2021) and smart farming (Escolar et al., 2019). According to Nurgaliyev & Saymbetov, (2020) and (Kim, 2019) one form of communication modules used for this is IEEE.802.15.4 modules. These modules which include Bluetooth, Zigbee and WiFi were used to create a Local Area Network so as to capture behavioural patterns in a network. Although, they are good for high data rate transmission and reception because they are characterized by large bandwidth, however, the downside of its application is that they are meant for short distance communication(Kim, 2019; Nurgaliyev & Saymbetov, 2020). Aside this, the power consumed by this devices will often time reduce the life of sensor nodes in the network where they are used. To overcome these ills, Low power devices were developed for wide area networks. These devices include LoRa/LoRaWAN, NB-IoT, SIGFOX and Wi-SUN FAN (Escolar et al., 2019). Among all these LoRa/ LoRaWAN is widely used today because of its efficient performance in ensuring wide range communication while using low power (Nurgaliyev & Saymbetov, 2020). Therefore, this infers that a LoRa Network is a network of wireless nodes which makes used of LoRa modules for communication.

The LoRa Network is made up of a LoRa module at the physical layer which is the first layer of the OSI model. While, the LoRa WAN specification describe the media access control protocol at the second layer of the OSI model. The technology, operating in unlicensed ISM band, uses Chirp spread spectrum pulses to encode the data transmitted during modulation. According to Escolar et al., (2019), this device is operated within 863-870 MHz in Europe, 902-928 MHz in the United State, 915-928MHz in Australia and 470-510MHz in China. One of the advantages of using this technology, is that LoRa divides the bands into different channels for uplink and down link (Escolar et al., 2019). Also, it is affirmed by Escolar et al., (2019), that for LoRa modules, longer bandwidth, results to longer data rates and lower transmission time. Networks which uses this technology is characterized with data rate which ranges from 0.3kbps to 27 kbps. This figure is as a result of a spreading factor (SF) ranging from 7 to 12.As shown in Fig. 3, with the use of LoRa WAN, devices can communicate directly with each other and with an internet connection. To communicate with the internet, the technology fosters communication with different gateways proving addressing and security.

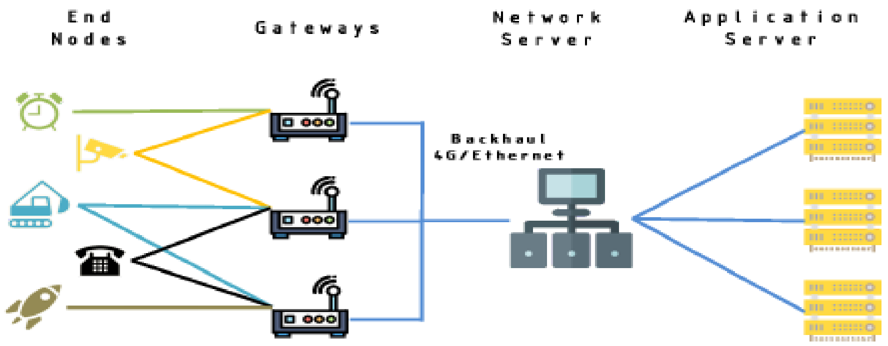


Fig. 3 – LoRa network (Kim, 2019)

3. System design

3.1 Network structure

The D2D network structure considered in this work is a point to point network communication. Figure 4 show that the network consists of two user equipment linked via wireless Lora connection. The characteristic of the network is such that these UEs could be static and could be mobile. These results in the variation of the signal strength which may lead to loss of data packet sent especially when one UE wonders away from the coverage area. It should also be noted that since there is no check on the received signal strength, both equipment could continue communication which contributes to the depletion of their battery, reducing the life cycle of the nodes. The use of LSTM in the network communication will forecast the distance between both UE. This will ensure that there is no loss in communication since the motion can be controlled. In this work, two scenarios are considered in which communication is assumed to take place for UEs moving apart or away from each other and UE moving towards each other.

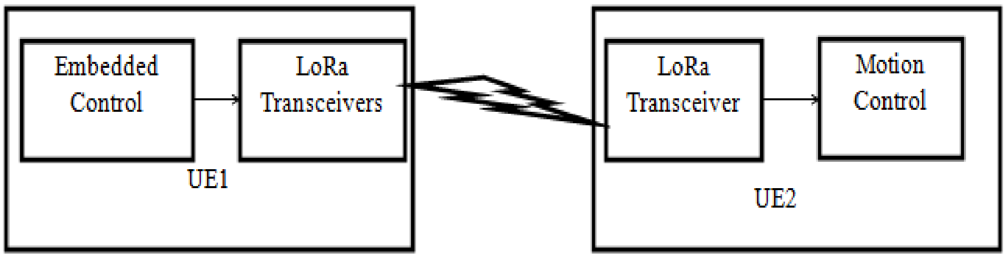


Fig. 4 – System structure considered

It is assumed that the D2D communication is on free space and that the battery level for each UE is enough to ensure maximum transmission. This however, is to ensure that the RSSI computed by the device is not affected by power. MATLAB will be used for simulation analysis. During the simulations, a scenario assuming static UE is considered. Furthermore, the future distance between the UE's is forecasted using the data generated from MATLAB. This will be achieved via the use of LSTM algorithm. The forecasting process will be achieved via the use of python embedded with packages such as tensor-flow, Keras, matplotlib, seaborn and pandas.

3.2 UE scenarios

In this work two scenarios have been considered as follows:

1) In this scenario, the mobile UEs as shown in Fig. 5 (a) and Fig. 5 (b) are seen to move away from one another. In Fig. 5 (a), the initial distance between the UEs is a. this is because the RSSI measured will be from UE a1 to UE b1. This is expressed as $RSSI = P_t - FSPL$. This same As a result the received signal strength is given as $RSSI_0$ and the path loss index is n_0. Therefore, the distance between the two UEs can be re written as:

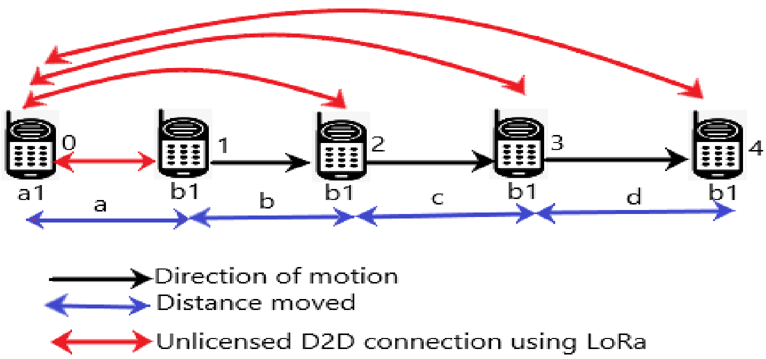
$$a = 10^{(A_0 - RSSI_0)/10n_0} \quad (1)$$

As UE b1 moves forward from position 1 to position 2, the total distance will be a+b. Also, the new received signal power will be A_1, with new received signal strength indicator $RSSI_1$ and new path loss index will be n_1. This therefor suggests that if the UE b1 moves from position 0to x, the distance measured between UE a1 and UE b1 at point x will be given as

$$a_x = 10^{(A_x - RSSI_x)/10n_x} \quad (2)$$

where x is the present position.

(a)



(b)

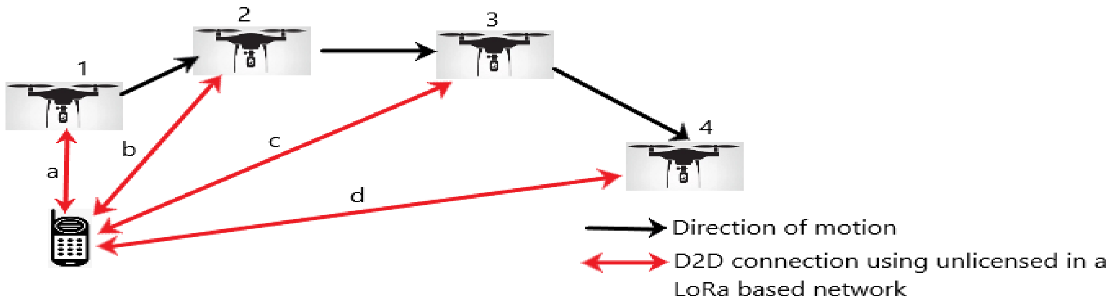


Fig. 5 – (a) Illustration of D2D LoRa based connection between user equipment moving apart from one another (b) D2D LoRa based connection between user equipment and drone.

In this scenario, the focus is on a D2D network with mobile user equipment which constantly move towards each other. As shown in Fig. 6, UE b1 is seen to move from position 4 to position 3 through to position 1. As a result of this movement, unlike scenario two where the power of received signal strength fades away, it is expected that the power of received signal strength increases as both UE a1 and b1 comes close to one another. Consequently, the distance via the use of received signal strength indicator RSSI will be expressed as $a_x = 10^{(A_x - RSSI_x)/10x}$. where a_x is the distance between a1 and b1 at point x in space. A_x is the power of the received signal, $RSSI_x$ is the received singal strength indicator at position x and n_x is the loss index at the point x.

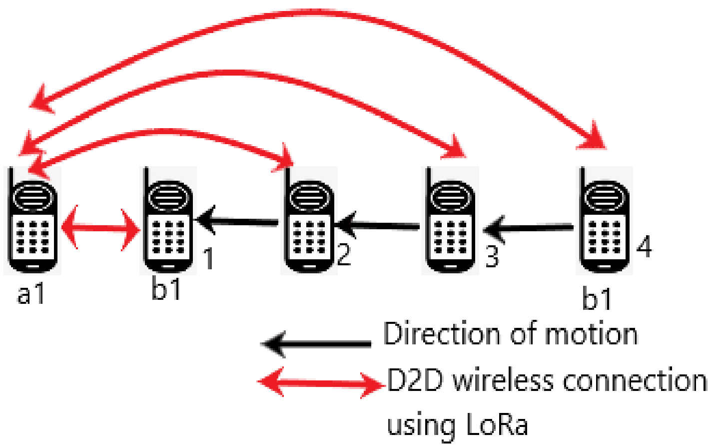


Fig. 6 – Illustration of D2D network with the UE b1 moving from position 4 to position 1

3.3 Parameters and data generation

In the quest to develop a MAT-Lab model to simulate the wireless communication of the two nodes using LoRa, the following parameters are considered important. Distance between the two nodes, transmit power, Path loss exponent, Shadowing standard deviation, thermal noise power, bandwidth and the RSSI threshold.

As stated by authors in Adi & Kitagawa, (2020) a typical Lora module can communicate within 100m to several kilometres away depending on how it is configured. This is the reason for using the minimum distance which is100m. The communication which is to last for 10 seconds is characterized with a sampling rate of 100Hz. In the simulation, it is assumed that the user equipment move at a speed of 10m/s. The transmit power of the LoRa module used is 14dB which is typical according to authors in Khan et al., (2022). The path loss exponent for free space as intended in this research is 2(Khan et al., 2022). Furthermore, in this study, the standard deviation due to shadowing for a line of sight considered is 3 (Fernando et al., 2015). The bandwidth and RSSI threshold are 125kHz and -104dB (Khan et al., 2022).

The data generated from the simulation of the three scenarios will contain features such as time stamp, RSSI, distance computed. In other words, the data generated is a series data which is suitable for forecasting. The data generated will be will be sliced such that 60% of it is used to train the LSTM model and forecast is made to see if the prediction matches the remaining 40%.

The data generated has to be pre-processed so as to be fit to be used to train an LSTM model. To achieve this, unwanted data columns are dropped leaving only time and the RSSI of both nodes. To be able to forecast the RSSI of each node when they are closed to each other or moving far apart, the data is subdivided into two to show the RSSI of each node at the various conditions. The trend of each of this situation is checked and the data scaled to have values between 0 and 1. The data which is structured to have input, feature and output is then further subdivided into training data and test data before being fed into the LSTM model.

3.4 Long Short Term Memory (LSTM)

Long Term Short Memory is a form of Recurrent Neural Network (RNN) that ensures the extraction and retention of long term variable in past data gathered (Nguyen et al., 2021).RNN characterized with three gates which includes control gate, input gate and forget gate, has more advantage over all method of forecasting (Muzaffar et al., 2019). Unlike the traditional neural network is used to produce Y variable when an input X is used at the input of the neural network and afterwards, Y is never used again, RNN uses the Y generated as the present X so as to forecast future Y. In other words, Y generated is not forgotten like the traditional neural network. As a result of this, RNN has to learn every past data which leads to a problem called the vanish problem. This means because the recurrent network has to learn all past data it tends to forget because the weight becomes too small for learning to occur. To solve this problem, LSTM was proposed as an improvement over RNN. The LSTM neural network overcomes the limitation of the RNN by propagating or forgetting information over a long and recurring training period (Singh et al., 2020). Furthermore, its ability to correlate between the previous and current information makes it suitable for time series data and achieve improved results (Singh et al., 2020). The basic architecture of LSTM model is a cell shown in Figure 3.7. The operation of this cell as presented by (Singh et al., 2020) is as follows:

Let $\boldsymbol{x_t}$be the sequence vector where index $t = 1, 2, \dots \dots T$ where T is the total time sample in the sequence. At time t the LSTM takes input sample from $\boldsymbol{x_t}$, past state $\boldsymbol{a_{t-1}}$ and past hidden state $\boldsymbol{h_{t-1}}$. At the input of the cell, the forget gate is what determines what is to be omitted from $\boldsymbol{x_t}$and $\boldsymbol{h}_{t-1}$. Note that the activation function could be a sigmoid or a rectified liner unit. The sigmoid which is often used at the input, output and forget gate is defined as $\sigma(z) = 1/1 + e^z$gives a value between 0 and 1 for any input z. at this point, the sigmoid function determines whether the input vector is to be propagated (having values closer to 1) or to be forgotten (having values close to 0). As the training of LSTM is on-going, gradient computation which may lead to gradient vanish can occur if the gradient shrinks to zero. This however is solved with the choice of rectified liner unit function which is defined as $\rho(z) = \max(z, 0)$. With this computation is made faster impeding the gradient to varnish. However the decision made by the forget gate on which information to be propagated or omitted from $\boldsymbol{x_t}$ and $\boldsymbol{h}_{t-1}$is what results to the output vector defined as:

$$\Gamma_f^t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \quad (3)$$

where $W_{fh}, W_{fx}$are matrix weight, f is the forget gate and b_f is the bias vector. Also, the resulting vector Γ_f^t is the resultant vector at the forget gate.This resulting vector (Γ_f^t) is what outputs 0 or 1 to determine what information is to be forgotten or propagated from cell state a_{t-1} via element product expressed as

$$a_t = \Gamma_f^t \odot a_{t-1} + \Gamma_i^t \odot \Gamma_g^t$$
(4)

WhereΓ_i^t, Γ_g^t are the resultant vector at the input gate and the input node.

The application of sigmoid function at the input gate yields a resultant vector expressed as

$$\Gamma_i^t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (5)$$

where W_{ih}, W_{ix} are matrix weight at the input gate and $b_i$is the bias of the input gate. The rectifier liner function applied at the input results to result vector expressed as

$$\Gamma_g^t = \sigma(W_{gh}h_{t-1} + W_{gx}x_t + b_g) \quad (6)$$

Where $W_{gh}\ and\ W_{gx}$are matrix weights at the input node and $b_g$is the bias of the input node

At this point the resultant elements Γ_i^t and Γ_g^t as represented in Eq. (4) contains new values to update a_t. Afterwards, the output gate passes the relevant values from updated a_t to as a new hidden state h_t. This is achieved by passing the updated $a_t$from the output gate through Rectified linear Unit (ReLU) function resulting to $\rho(a_t)$. Afterwards, the location of the updated cell state vector which holds the filtered values are decided by sigmoid function to yield the resultant element at the output gate expressed as

$$\Gamma_o^t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (7)$$

Using the element wise product Γ_o^t and $\rho(a_t)$, new hidden state is finally expressed as

$$h_t = \Gamma_o^t \odot \rho(a_t)$$
(8)

All these procedures are used to learn hidden features of the data used.

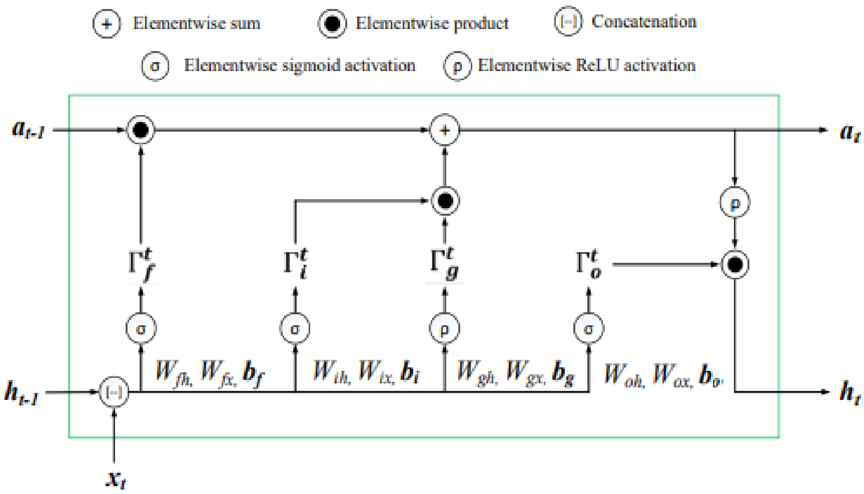


Fig. 7 – Illustration of LSTM cell structure (Singh et al., 2020)

3.5 Procedures in the application of LSTM

The application of LSTM aids the prediction of the next series in the time series data. To achieve this, steps as shown in the Fig. 8 will be applied. First the accumulated data is read or gathered so as to be formatted. The formatting also called data pre-processing or data preparation involves the mapping of all data points gathered into features (X) and target (Y).

If the time series data is generated is a univariate sequence such as $[a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, \ldots \ldots \ldots . . a_n]$, the data is then formatted so into X and Y as shown in Table 1. As illustrated, a_0, a_1, a_2 is used to determine the next sequence which is a_3. The data input a_1, a_2, a_3 is used to predicta_4. Therefore, $a_{n-2}, a_{n-2}, a_{n-1}$ will be used to predict a_n.

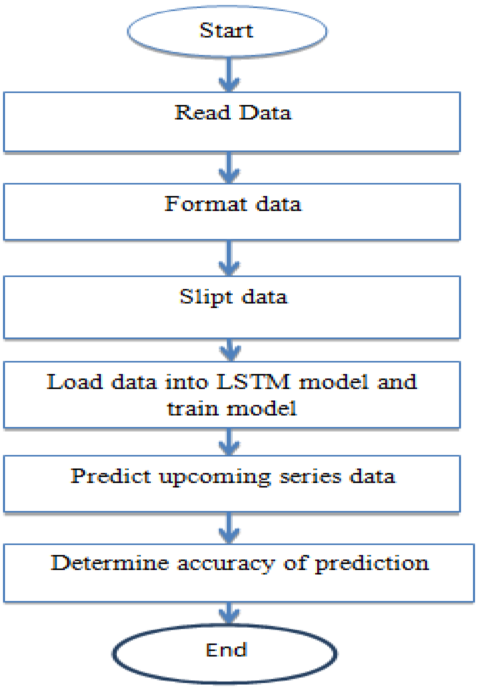


Fig.8 – work flow of the process involved in prediction

Table 1 Format of the data to be trained in an LSTM model.

X	Y
$\boldsymbol{a_0}, \boldsymbol{a_1}, \boldsymbol{a_2}$	a_3
$\boldsymbol{a_1}, \boldsymbol{a_2}, \boldsymbol{a_3}$	a_4
$\boldsymbol{a_2}, \boldsymbol{a_3}, \boldsymbol{a_4}$	a_5
$\boldsymbol{a_3}, \boldsymbol{a_4}, \boldsymbol{a_5}$	a_6

After the preparation of the data in the format as illustrated in table 1, the data is sheared into training data and test data. It is important to note that there are no standard ways of data being shared. In this research the training data will be 80% of the data prepared. This is done so as to aid the prediction from a known dataset which is the remaining 20% of the data to the unknown dataset which is what will be forecasted. The training data set is then loaded in the LSTM model. Afterwards, training is conducted and predictions of future sequence are carried out. With this, it will be possible to know when the mobile D2D will stray out of range of communication in an unlicensed spectrum. All these processes are done with python.

4. Results and discussion

This section presents the effect of distance on Received Signal Strength (RSSI) and the path loss in a D2D communication. The scenarios considered were when both nodes are moving towards one another and when the nodes are moving away from each other. Data of the RSSI was gathered and used to train an LSTM model to see how best it can be forecasted.

The results of the behaviour of the network as a result of the nodes moving towards or away from each other are presented. The results generated include the distance between the nodes, the RSSI and the Path Loss. Figures 9 to 11 respectively show the graphical plots.

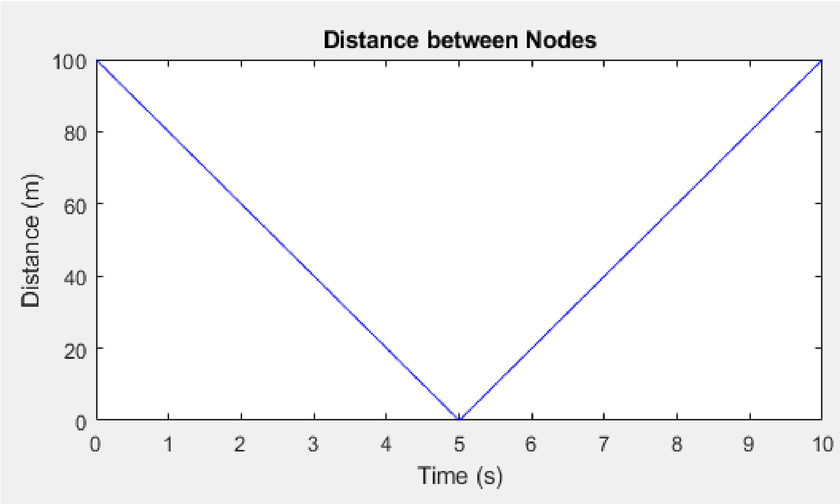


Fig. 9 – Graphical illustration of the distance between the two nodes

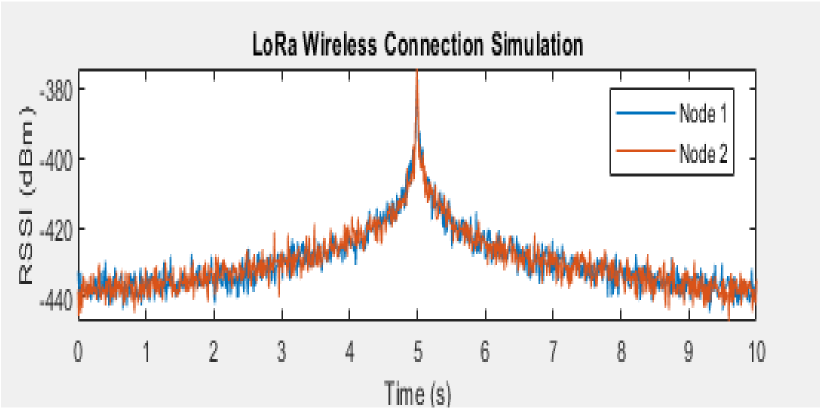


Fig. 10 – Graphical illustration of the RSSI of both nodes with respect to time

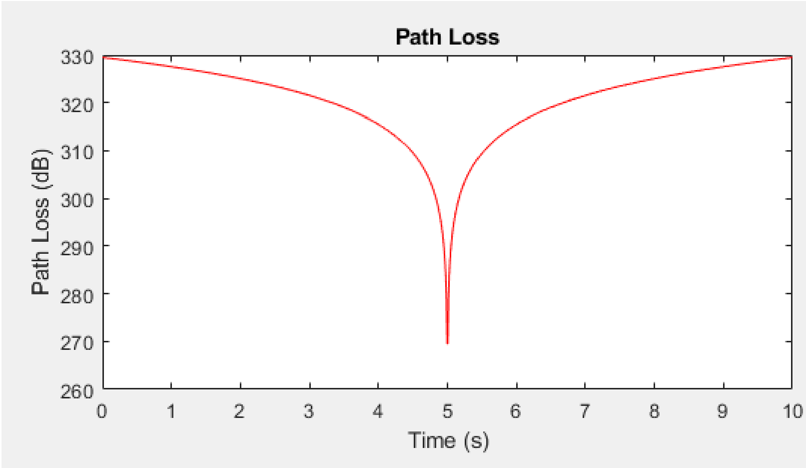


Fig. 11 – The Path loss experience during communication as a result of motion

As a result of the simulation, the RSSI of both nodes and the path loss and the location of each node was collected in excel and was saved in CSV format. This is shown in Table 2. With this, the second objective is achieved.

Table 2 Data collected from the simulation

	Time	RSSI_Node1	RSSI_Node2	PathLoss	Distance	Location_Node1	Location_Node2
0	0.00000	-440.669769	-445.854640	329.488200	100.000000	0.0000	100.0000
1	0.01001	-429.466306	-441.950387	329.470794	99.799800	0.1001	99.8999
2	0.02002	-439.759313	-433.253499	329.453352	99.599600	0.2002	99.7998
3	0.03003	-436.732407	-439.837273	329.435876	99.399399	0.3003	99.6997
4	0.04004	-452.762851	-449.527012	329.418364	99.199199	0.4004	99.5996
...	...	...	...	...	...	...	...
995	9.95996	-438.023043	-437.588618	329.418364	99.199199	99.5996	0.4004
996	9.96997	-440.360734	-443.929339	329.435876	99.399399	99.6997	0.3003
997	9.97998	-431.933037	-446.579167	329.453352	99.599600	99.7998	0.2002
998	9.98999	-441.612851	-436.306086	329.470794	99.799800	99.8999	0.1001
999	10.00000	-438.015055	-439.717422	329.488200	100.000000	0.0000	100.0000

Figure 9 presents the distance between the two nodes. From the figure it is observed that initially, the distance between the nodes was 100m. However, as a result of the nodes moving towards each other, both nodes where together when time = 5 seconds. Afterwards, both continued to deviate from one another till they were 100m apart. As a result of this movement, it is observed that the RSSI of both nodes started increasing until it peaks in Fig. 10. As the nodes stared moving apart, a decline in RSSI is noticed too. This movement also, is seen to affect the path loss as the loss declines as both nodes come close to one another and increases as they move away from each other.

Figures 12 and 13 shows the data in graphical form being subdivided into RSSI data of both nodes plotted with respect to time as they move towards each other. Node 1 is denoted as red while node 2 is represented as blue. This was achieved after dropping unwanted columns in the data. Figures 14 to 17 present the graphical representations of each node increasing in RSSI and decreasing in RSSI as the move towards each other and move away from each other.

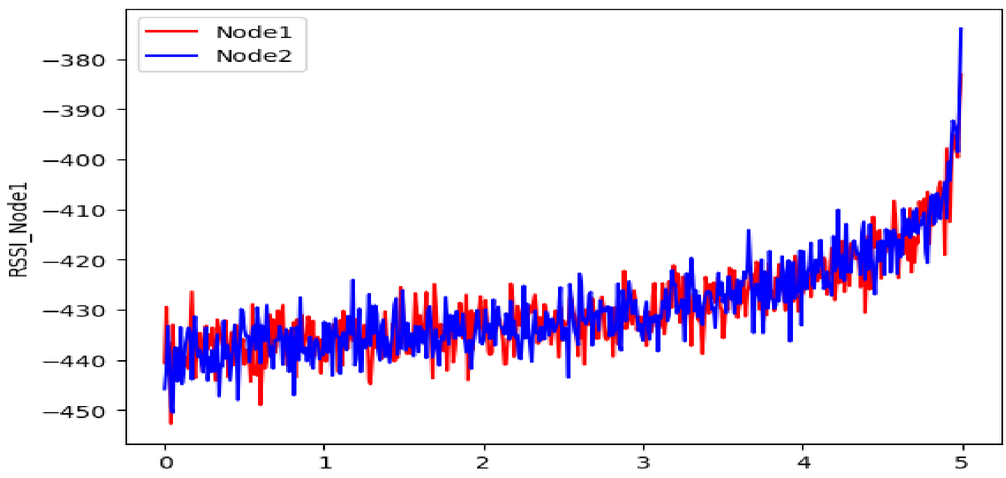


Fig. 12 – Graphical representations of the RSSI data with respect to time when the nodes were moving towards each other

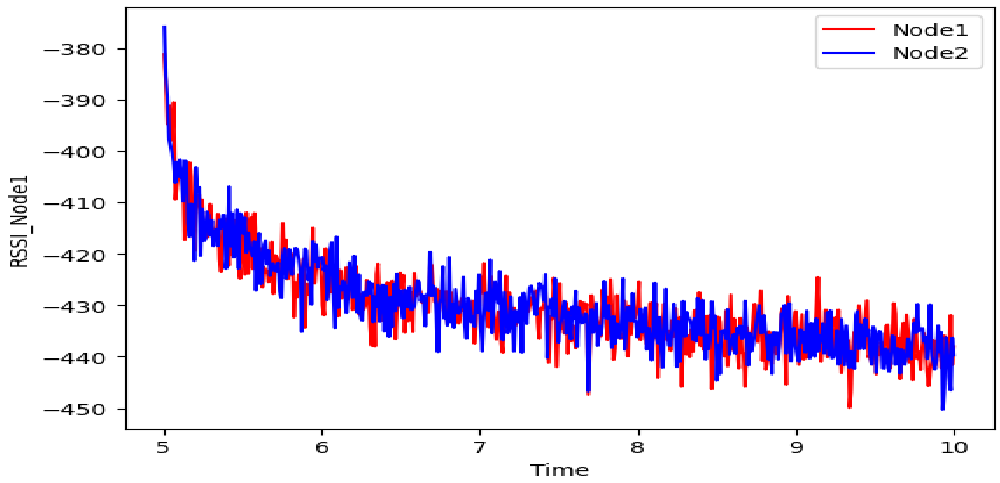


Fig. 13 – Graphical representations of the RSSI data with respect to time when the nodes were moving away each other

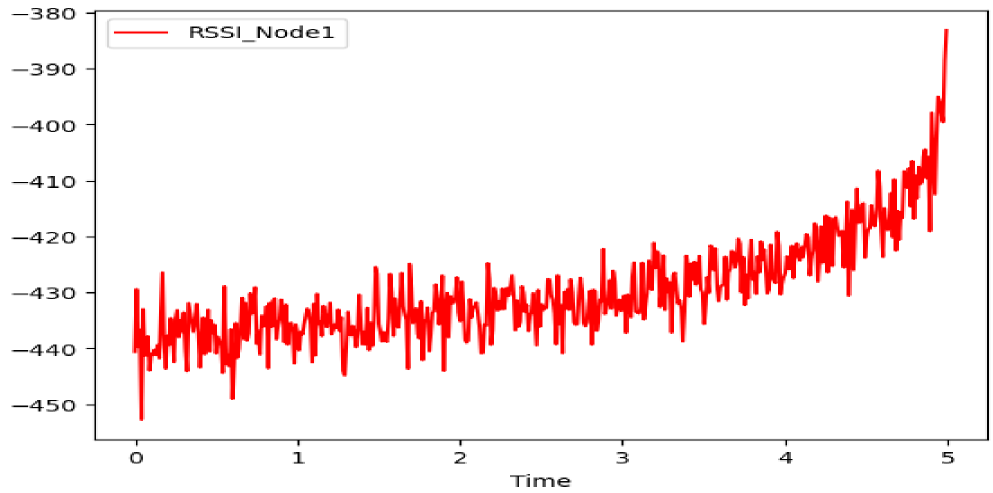


Fig. 14 – Graphical representations of the RSSI data of node 1 with respect to time when nodes 1 approaches node 2

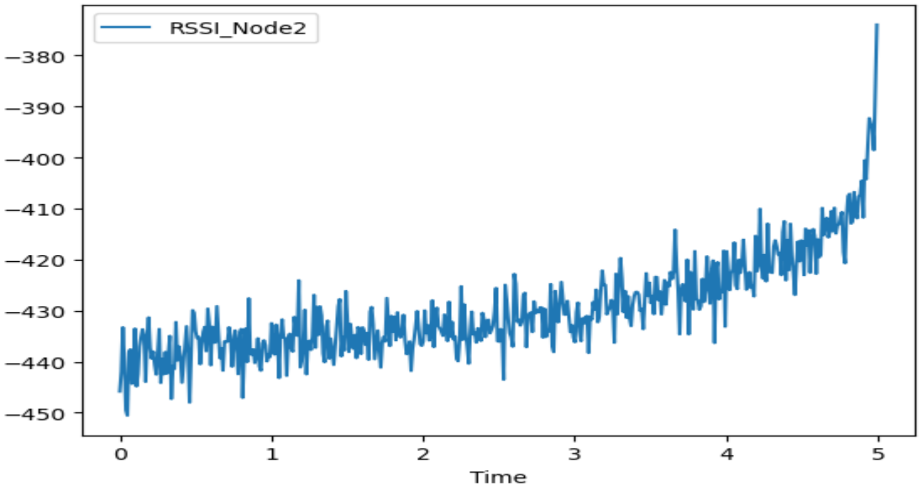


Fig. 15 – Graphical representations of the RSSI data of node 2 with respect to time when nodes 1 approaches node 2

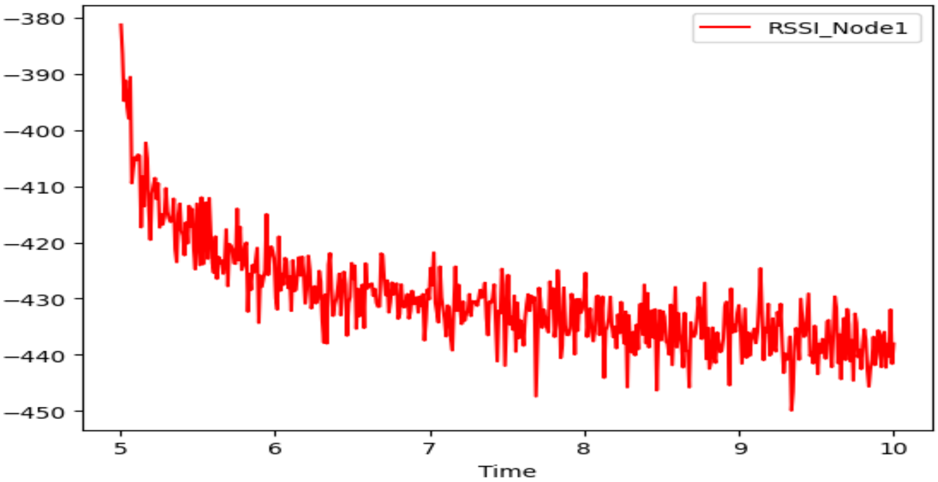


Fig. 16 – Graphical representation of the RSSI data of node 1 with respect to time when node 1 is moving away from node 2

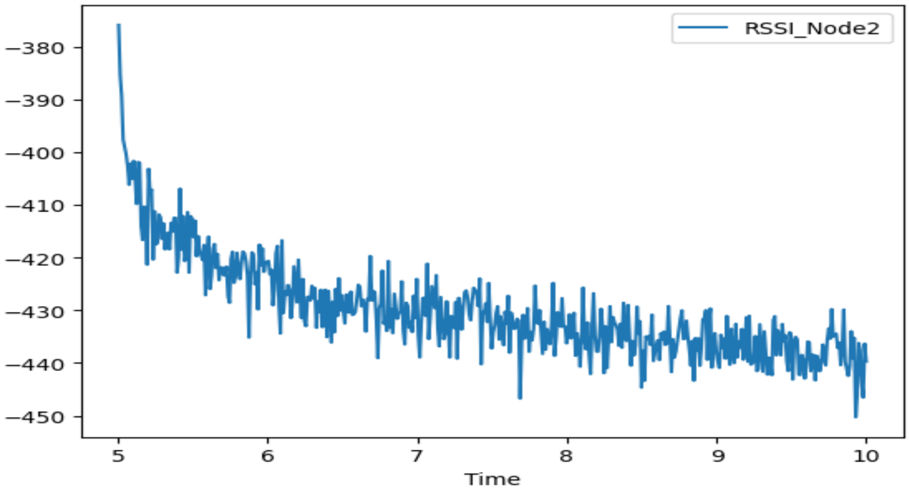


Fig. 17 – Graphical representation of the RSSI data of node 2 with respect to time when node 1 is moving away from node 2

Figures 18-21 present a graphical representation of the decomposition of the RSSI signal with respect to time. Each includes a sub chart of the RSSI (a), the trend chart (b), the seasonality chart (c) and the residue (d). The trend line in Fig. 18 and 19 show the upward trend. This implies an increase in RSSI. While in Fig. 20 and 21 shows a downward trend implying a decrease in the RSSI of the nodes. All the charts shows a horizontal straight line seasonality when the noise or residue is removed.

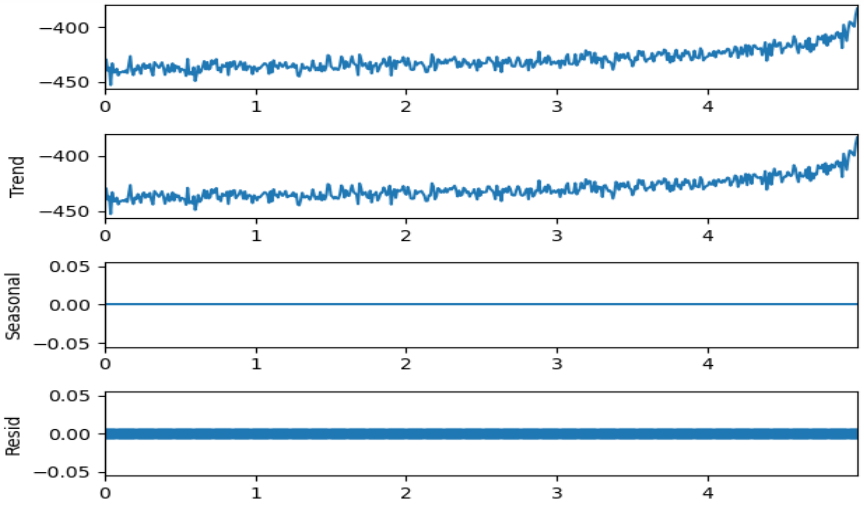


Fig. 18 – Graphical representation of Node 1 decomposed when moving node to node 2

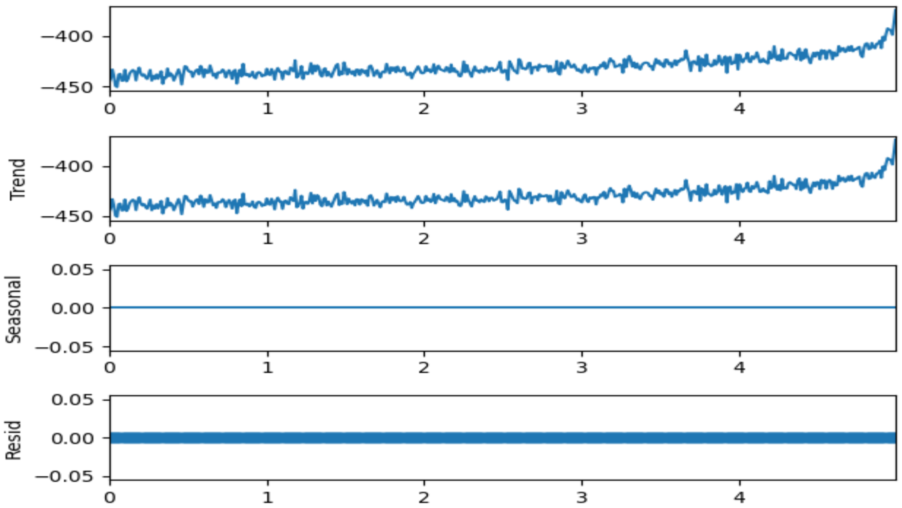


Fig. 19 – Graphical representation of Node 2 decomposed when moving node to node 1

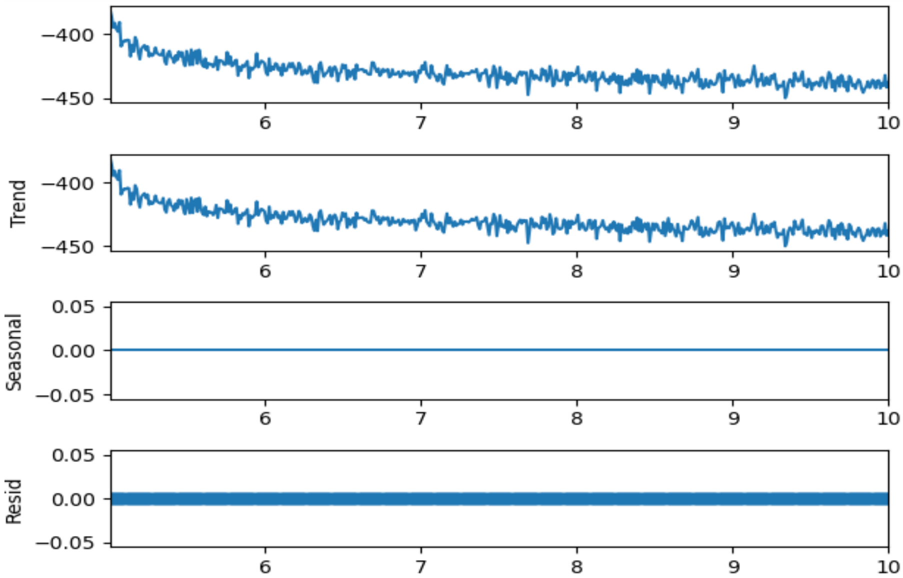


Fig. 20 – Graphical representation of Node 1 decomposed when moving away from node 2

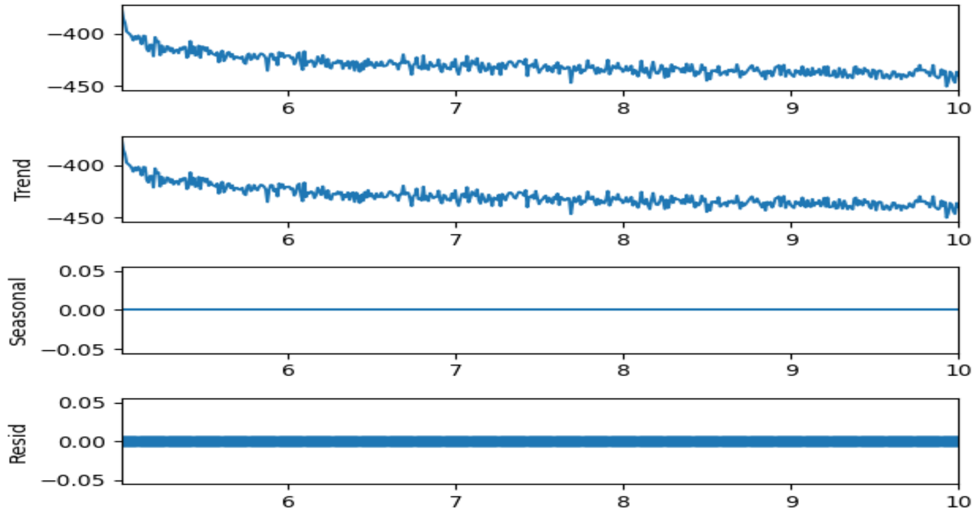


Fig. 21 – Graphical representation of Node 2 decomposed when moving away from node 1

Table 3 presents the summary of the LSTM model. As shown in the table, the data is fed into 80 neuron and at the end it produces one output at the second dense layer.

The table 4.2 Table showing the model summary

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_1 (LSTM)               (None, 80)                26240

 dense_1 (Dense)             (None, 1)                 81

=================================================================
Total params: 26,321
Trainable params: 26,321
Non-trainable params: 0
_________________________________________________________________
```

Each training data is fed into the model and trained with 60 epochs after which the loss is computed. The loss represented shows the loss reduced from 0.010 to 0.006 for Fig. 22 and Fig. 23. Also, the loss when both are moving away from each other reduced from 0.008 to 0.0045 for Fig. 24 and reduces from 0.0065 to 0.0035 for Fig. 25. This means that there was no need to train further.

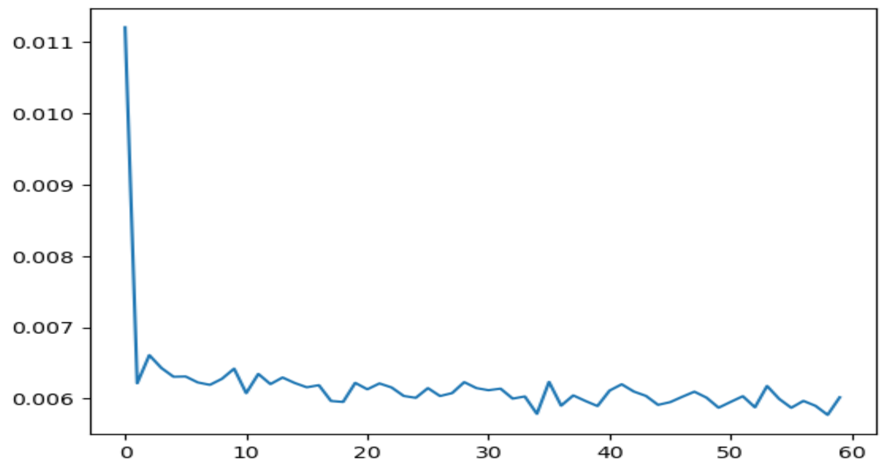


Fig. 22 – Graphical representation of the loss per epoch of the RSSI of node 1as the two nodes approach each other

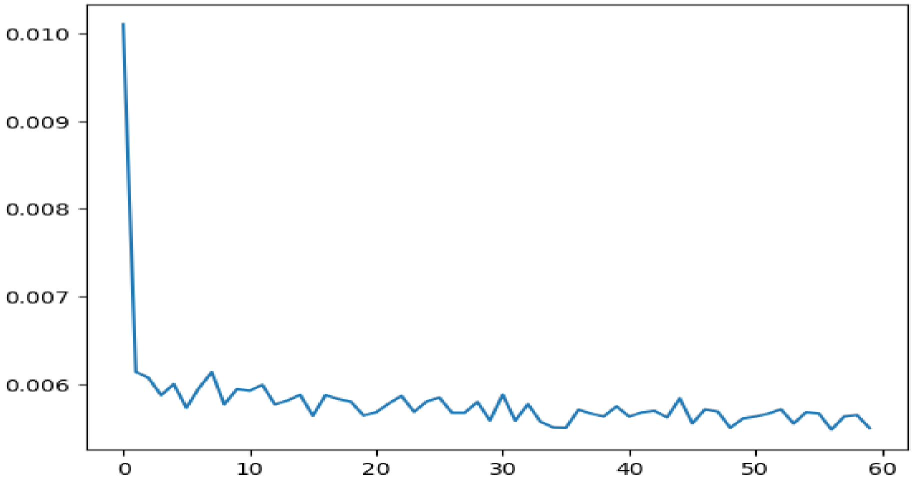


Fig. 23 – Graphical representation of the loss per epoch of the RSSI of node 2as the two nodes approach each other

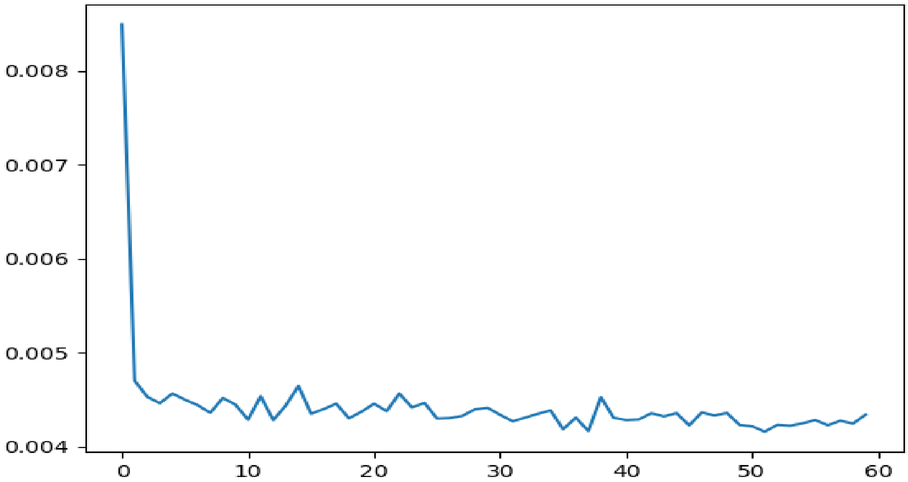


Fig. 24 – Graphical representation of the loss per epoch of the RSSI of node 1 as the two nodes move away from each other

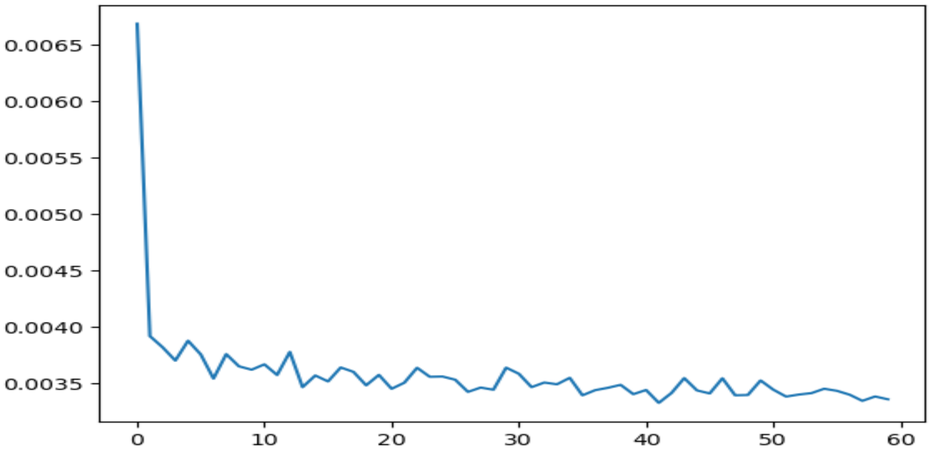


Fig. 25 – Graphical representation of the loss per epoch of the RSSI of node 2 as the two nodes move away from each other

For the four cases, forecasting of the remaining data was done and it was compared with the test data. This is represented in Fig. 26-29. As shown in these figures, the predicted data was not too different from the test data even though at some points the predicted and the test data seem not following the same pattern. The root mean square error of the predicted RSSI of node 1, when moving towards node 2 is 4.848 while the root mean square error of the predicted RSSI for node to moving towards node 1 is 5.153. Furthermore, the root mean square error of node 1 when moving away from node 2 is 4.68 while that of node 2 is 4.17. Conclusively, both the test and forecasted data have same trend.

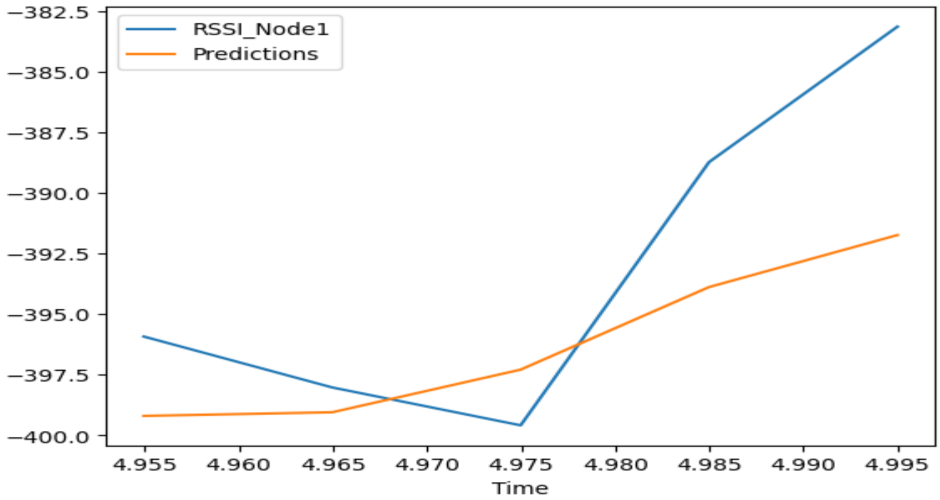


Fig. 26 –Graphical representation of test value and predicted value of RSSI data of node 1 when moving towards node 2

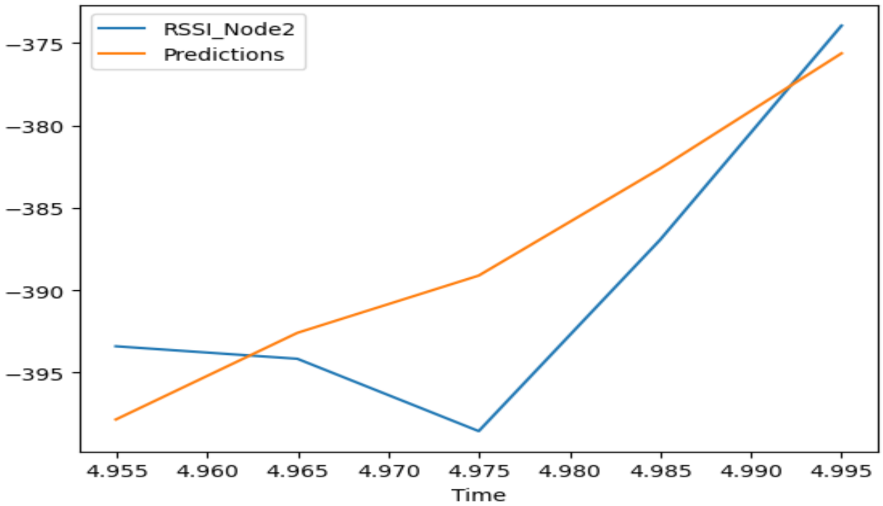


Fig. 27 – Graphical representation of test value and predicted value of RSSI data of node 2 when moving towards node 1

.

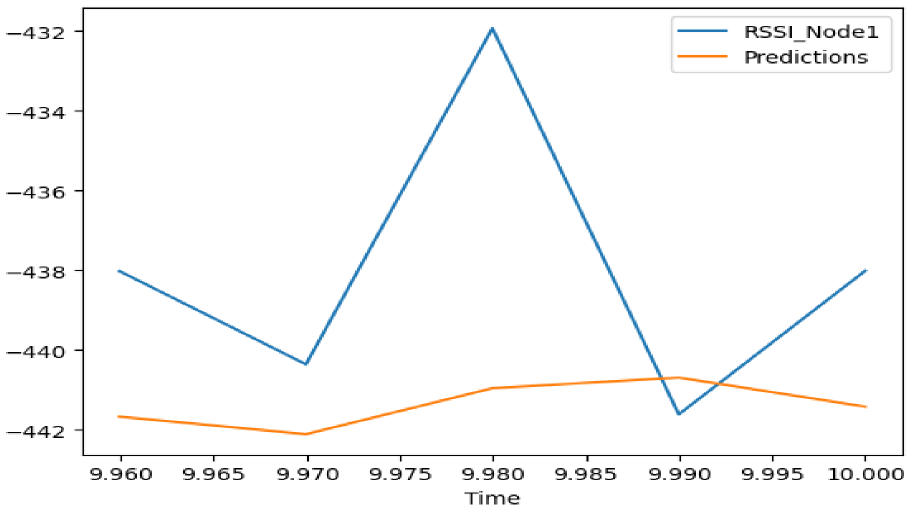


Fig. 28 – Graphical representation of test value and predicted value of RSSI data of node 1 when moving away from node 1

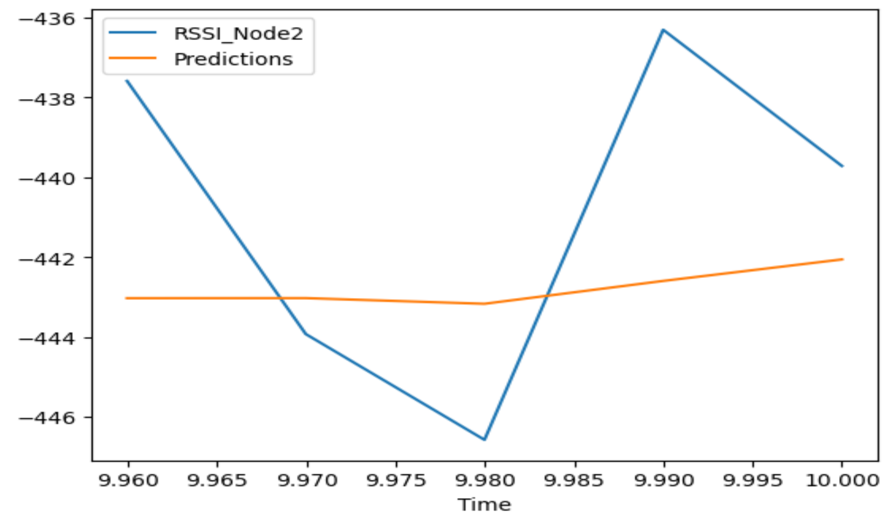


Fig. 29 – Graphical representation of test value and predicted value of RSSI data of node 12when moving away from node 1

Conclusively, the Received Signal Strength (RSSI) and the path loss in a D2D communication have been presented. In the quest to ensure proper communication between a device to device networks, the study presented a method to pre-empt the behaviour of a LoRa based D2D network. To achieve this, user equipment which is assumed to communicate in a line of sight situation was simulated using MATLAB. The scenarios considered were when both nodes are moving towards one another and when the nodes are moving away from each other. Data of the RSSI was gathered and used to train an LSTM model and forecast was made using same model. It was observed that the forecast was following the same trend with the test data with RMSE of 4.848, 5.153 for each node when moving towards each other and RMSE of 4.68 and 4.17 when moving apart.

Acknowledgements

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