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# Comparative Analysis of ANN-Based Mobility Prediction Performance in an Ad-Hoc Network

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**Abstract**— The facility of arbitrary node movement one side has advantages on application on the other side very difficult to manage the network because random node mobility directly effects on network connectivity and interrupt on the performance, obtained challenges like routing overhead, packet losses, increases energy consumption, wasted bandwidth for reconnection, decreases throughput etc. Thus an accurate mobility prediction of a node before leaving one position to another or subsequence position can be improve network performance which is effects by node mobility. Now day's artificial neural networks (ANNs) is very common and trending for approximation and prediction application and also popular for node trajectory prediction. In this paper we explore the architectures of some static (like MLP and RBF) and dynamic (like FTDNN, DTDNN, NARX and LSTM) neural network and search best ANN model by obtaining optimal model parameters to predict node mobility and compared the performance using mobility model (Gauss Markov model) dataset as well as real-world dataset collected from Crawdad to highlight generalization capabilities. Mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and average coordinates distance error (DE) between observed and estimated positions are used to evaluate their performance. The empirical results show that LSTM is the best artificial neural network (ANN) model for mobility prediction in both model based and real-world dataset(testing sets).

**Keywords**- Mobility Prediction, MLP, RBF, FTDNN, DTDNN, NARX, LSTM.

## I. INTRODUCTION

Ad hoc network technology now a days growing fast in modern society and increasing demand with quality of experiences in real life application such as in defense, disaster rescue, campus or mall, hospital, smart vehicular, robotics and in smart home etc. In order to meet the required demand ad hoc network technology need to planning and management of highly dynamic node mobility by providing efficient and reliable network performance. Mobility prediction is the main factor in ad hoc network to meet efficient and reliable network management, because the node mobility directly effect on network link connectivity and interrupt the established network frequently and results to reconfigured or to reorganized increases overhead, decreases throughput and waste resources like battery, bandwidth etc. However, an accurate mobility prediction in advance of subsequence position of mobile node can overcome the challenges and improve the network performance.

The mobility prediction means calculation of future position of geographical coordinates using past and present positon of coordinates. In an ad hoc network, each node is aware of its location and records it for a set period of time using node embedded GPS (Global positioning system) and it is called node trajectory, this node trajectory used for calculation of future position [1][2]. Many methods are used for mobility prediction in early among these method ANN is the most popular and widely used due to its learning and generalization capabilities.

The study's primary objective is to find suitable Artificial Neural Network (ANN) models by finding optimal network parameters to predict the future node position based on the available trajectory data. And, to find which predictor models gives better prediction results. For guiding research formulated two research question and research motivation as follow

*Research Questions:*

**RQ 1:** What Artificial Neural Network (ANN) models are appropriate for predicting node trajectory data?

**Motivation:** This research question was made with the goal to find Artificial Neural Network (ANN) models to predict the node future position.

**RQ 2:** In predicting the future position of the node, how do

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Artificial Neural Network (ANN) models perform differently?

**Motivation:** This research question was made with the goal to evaluate the performance of the selected predictors' model.

To fulfil the objective and research question as mansion above in this paper we, investigate and compare the performance of some static (like MLP and RBF) and some dynamic (like FTDNN, DTDNN, NARX and LSTM) neural networks in the application of mobility prediction using node trajectory dataset.

## II. Literature Review

Earlier there are several research studies that used artificial neural network to predict mobility prediction in ad hoc network environment. In table 1 shows six recent studies in application of mobility prediction.

In [3] proposed deep learning algorithm back propagation through time (BTT) adding more hidden layer in multilayer neural network to predict node mobility using the received signal strength (RSS) value and test the predictor model using random waypoint mobility (RWM) dataset in MATLAB 2017a tool and The outcome indicates that the relationship between the output and the target is R=1, which denotes a precise linear relationship between the two.

**Table 1** summary of literature review

| Ref | Networks | ANN Models | ANN Architecture | Transfer function(TF) | Training Algorithm (TA) | Dataset (Trajectory) | Performance Measures | Predict |
|---|---|---|---|---|---|---|---|---|
| [3] | MANET | Deep MLP | 6-5-6 | Sigmoid(tansig) | BPTT | RWM, RSS | MSE, R | Link |
| [4] | ON | LSTM-RNN | | Sigmoid, Tanh | Adam | Real data iMote traces Cambridge University campus and MIT | Accuracy | Link |
| [5] | Human Mobility | LSTM and Seq2Seq LSTM | 2-128-128-128-2 | Sigmoid, Tanh | BPTT | Model based dataset(SLAW & SMOOTH) and GPS trajectory Geolife project real-world data | MSE, Geographical distance error | Location |
| [6] | MANET | ARIMA & RNN | | Sigmoid | BP | RWM | MSE, RMSE, MAE | Node Speed |
| [7] | MANET | LSTM | | Sigmoid, Tanh | | RWM | RMSE | Location |
| [8] | MANET | FFNN | 4-13-1 | Sigmoid | BP | | | Position |

Recurrent neural network (RNN) based link prediction of nodes in opportunistic network using long short term memory (LSTM) model [4] with the help of information of vector sequence node data and node pair historical information at different movement. The effects of performance parameters are investigate to design best prediction model using Cambridge and MIT campus reality dataset, the result shows that at 40 iterations with 5 input sequence length, the recurrent neural network link prediction (RNN-LP) has stable and accuracy decay to fix and model is better than local path and resource allocation methods.

Compare the human mobility position based on deep neural network [5], first standard LSTM model used for position prediction using mobility model data such as SLAW and SMOOTH, the result for specific user LSTM model best performance but in case of multi user multistep prediction obtained issue like computational over head for specific user training and error accumulation effect for multi-step prediction. Seq2Seq LSTM based region wise predictor model proposed and results reveal that this model is superior that others predictor methods.

The authors in [6] proposed futuristic node speed prediction in MANET using ARIMA and RNN model. Three different node speed scenarios consider i.e. walking, running and cycling to evaluate and when the performance of the predictor's model based on ARIMA, RNN, and other existing models is compared, the ARIMA model scored a speed prediction precision rate that was 17 to 24 percent higher than other existing works.

In [7] mobility predictor's model is frame for MANET using ARIMA and LSTM-RNN to extend route maintenance and improve throughput by mobility prediction or reducing link failure. Compared ARIMA and LSTM-RNN based prediction performance and authors reveal that LSTM is suited for large time series data prediction than ARIMA.

In [8] the author's proposed routing technique in MANET with the help of ANN based mobility prediction. The method achieved with modules of steps, first step setting up all

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MANET nodes in cluster and most stable node are selected cluster head remaining node of each cluster become member of the cluster. Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm are used for clustering setup, after setting up node cluster the mobile node prediction technique is apply using feed forward neural network and this predicted node position used for routing packet and the result show that the packet success ratio, throughput and bandwidth increase 20%, 25% and 27% respectively.

## III. METHODOLOGY

To achieve the objective explore artificial neural networks and search the optimum model parameters for mobility prediction application, a small varying model parameters give varying network performance. There is no specific method to find optimal network parameters, so we obtained optimal complexity model using error and trail method. For testing and to highlight the generalization capabilities we used mobility model based dataset as well as real-world dataset.

### *3.1. Mobility model data traces*

Model based mobility data generated using BonnMotion tool which is a Java based simulation platform allowed to create several model based mobility scenario [12]. However, we generate Gauss-Markov model based mobility data due to its realness character of node movement. Each node position traces for 4000 second in a simulation area 1000m X 1000m and recorded node position at a fix interval of time 5 second, as define node trajectory. Node trajectory need some preprocess and we perform the subsequent preprocessing actions. Firstly we normalized generated data between 0 to 1 using following formulas as in equation 1

$$D_{nor} = \frac{D_o}{D_{max} - D_{min}} \tag{1}$$

where, $D_o$ is observed data, $D_{\max}$ , $D_{min}$ maximum and minimum of observed data [9]. Secondly segmented the data series in the fix interval of time 5second, at last created training dataset input sequence and target sequence using sliding window of size $w = 3$ [5] [10]

$$input = [P_1, P_{2,}, \ldots, P_{n}]$$

$$target = \frac{1}{w}\sum_{t=n-w+1}^{n} P_t(x, y) \tag{2}$$

Where $P$, $w$ and $n$ are denote node position at time $t$, window size and length of data sample respectively.

### *3.2. Real-world data traces*

Real-world data traces obtained from Crawdad contributed by Gray et al [13] outdoor experiment of MANET at athletic field utilizing four different routing algorithms with one master node, 40 common nodes, and of authors proposed compare the performance of four routing algorithm. However, we used position capture of one ordinary node trajectory to assess the performance neural network based mobility predictors model. The capture trajectory raw data presented series of latitude and longitude geographical coordinates attached with time stamp recorded by GPS which is necessary to preprocess, so we perform the subsequent preprocessing operations. First, we use a particular coordinate projection to translate the geographic coordinates represented by latitude and longitude into two-dimensional plane (x, y) coordinates. Secondly plane $(x, y)$ coordinates series data normalized in between 0 to 1 using equation 1. Thirdly segmented the data series in a fix interval of time 5 second and at last created training dataset using equation 2 [5].

### *3.3. Performance measures*

In this paper we, used four measure metrics mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and geographical distance error (DE) between observed and predicted data to evaluate the performance of the predictors model and that are calculated by the following equations [11] [5]

$$MSE = \frac{1}{n} \times \sum_{t=1}^{n} (P_t - \hat{P}_t)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{t=1}^{n} (P_t - \hat{P}_t)^2} \tag{4}$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| P_t - \hat{P}_t \right| \quad 5)$$

And

$$DE = \sqrt{(P_t x - \hat{P}_t\, x)^2 + (P_t y - \hat{P}_t\, y)^2} \quad (6$$

Where $P_t$ and $\hat{P}_t$ are observed and predicted position respectively. $n$ is length of sample size.

## IV. EXPERIMENT SETUP

Several factors and parameters (such as the hidden layer, training technique, activation function, hidden layer neuron, etc.) that affect the performance of the node mobility prediction problem call for in-depth research and analysis. The prediction performance of the predictor model is then assessed against both the model-based and real-world mobility datasets after the optimal design parameters have been identified experimentally. Throughout the studies, the total 720 node mobility positions across an hour that were recorded in 5-second intervals were divided into training and testing portions of 70% and 30%. Predictor models are created using both default values from the MATLAB Tool Box and ideal network parameters that are found through trial and error. Create a hidden layer, two outputs, and inputs that are just two dimensions. The network was trained for a maximum of 1000 epochs. In the neural network (NN) toolbox, the default learning rate (0.005) and stopping criteria were established. Predictor models based on MLP, FTDNN, DTDN, and NARX employed a linear transfer function for the output layer and a hyperbolic-tangent transfer function for the hidden layer. The second-order Bayesian regulation backpropagation technique was used to train the network with 15, 14, 15, and 15 hidden layer neurons, respectively. For the newrb, newrbe, and newgrnn functions of the Gaussian radial basis function-based mobility prediction models at different spreads, such as 1, 1, and 0.07, respectively. A maximum of 250 epochs, a gradient threshold of 1, an initial learn rate of 0.005, a "piecewise" learn rate schedule, a "learn rate drop period" of 125, a "learn rate drop factor" of 0.2, and "CPU" as a hardware resource for the training are also used for training sgdm, rmsprop, and Adam-based LSTM mobility predictor models. Finally, the predictor models were run on MATLAB 2018a on a 64-bit OS with an Intel Core i3 CPU and 4 GB of RAM.

## V. Comparative Analysis Of Performance Results

Using MSE, RMSE, MAE, and DE as assessment metrics, dynamic prediction models like FTDNN, DTDNN, and NARX, as well as sgdm-based LSTM, rmsprop, and adam-based LSTM, are contrasted with static neural networks like MLP and other RBF functions. The fit between what was observed and what was predicted can also be measured using regression analysis on training sets and testing sets. We employed two datasets, namely mobility model data and real-world trace data, to assess the proposed mobility predictor models' capacity for generalization.

### *5.1. Mobility prediction analysis using gauss markov mobility model dataset*

A mobility model dataset containing performance metrics for MSE, RMSE, MAE, and DE is used to analyze the performance of mobility predictor models. This section also analyses the network regression value R for the training and testing sets.

*(a). Based on Mean Square Error (MSE)*

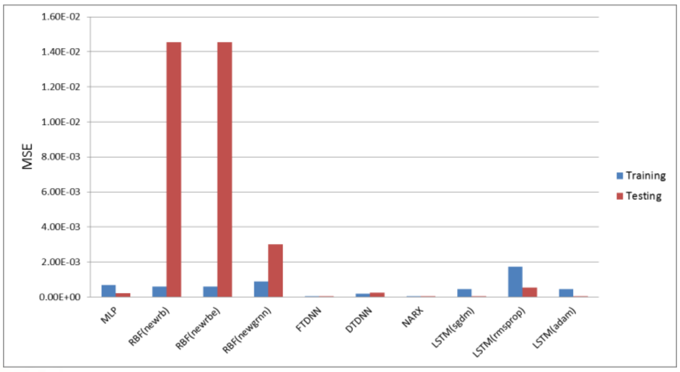


**Figure 1:** Analysis of prediction performance considering MSE using mobility model dataset

Figure 6.1 depicts the performance analysis of mobility predictor models considering MSE with training and testing sets using mobility model dataset. For training sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.002438, 0.002196, 0.002196, 0.002279, 7.08E-05, 4.24E-04, 6.59E-05, 1.80E-04, 5.58E-04, 1.90E-04. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 5.29E-04, 7.26E-04, 7.26E-04, 8.90E-04, 7.21E-05, 6.10E-04, 2.10E-04, 1.56E-05, 1.90E-04, 3.57E-05.

*(b). Based on Root Mean Square Error (RMSE)*

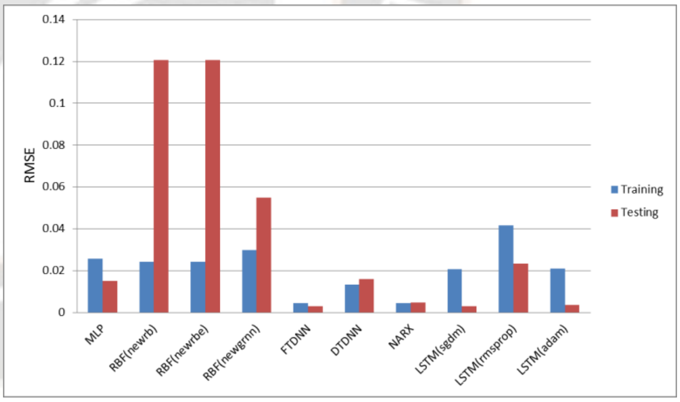


**Figure 2:** Analysis of prediction performance considering RMSE using mobility model dataset

Figure 6.2 depicts the performance analysis of mobility predictor models considering RMSE with training and testing sets using mobility model dataset. For training sets, the RMSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.049377, 0.046871, 0.046871, 0.047744, 0.008416, 0.020601, 0.008116, 0.013416, 0.023627, 0.013795.

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For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.023000, 0.026952, 0.02953, 0.029829, 0.008491, 0.024701, 0.014496, 0.003952, 0.013779, 0.005978.

The above discussion shows that dynamic neural network provides better performance than the static neural network models due to presents of time delay which help to memorized the time sequence node positions and provides the previous information to predict the future node positions. In the training phase NARX scored lowest error followed by FTDNN on the other hand in the testing phase less error score by sgdm based LSTM followed by adam based LSTM. Training with a very small error can affect the generalization ability of the predictor models, so we choose the generalization error or testing error as the criterion in the selection of the ANN predictor model.

*(c). Based on Mean Absolute Error (MAE)*

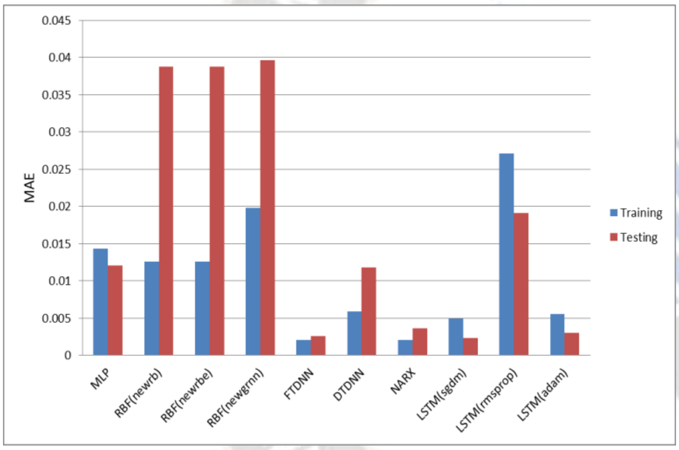


**Figure 3:** Analysis of prediction performance considering MAE using mobility model dataset

Figure 6.3 depicts the performance analysis of mobility predictor models considering MAE with training and testing sets using mobility model dataset. For training sets, the MAE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are , 0.038642, 0.036710, 0.036710, 0.037117, 0.006329, 0.015717, 0.006150 0.007946, 0.018243, 0.008688. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.017904, 0.021277, 0.021277, 0.023458, 0.007060, 0.019952, 0.011921, 0.002969, 0.010819, 0.004937.

*(d). Based on geographical coordinates (average) distance error (DE)*

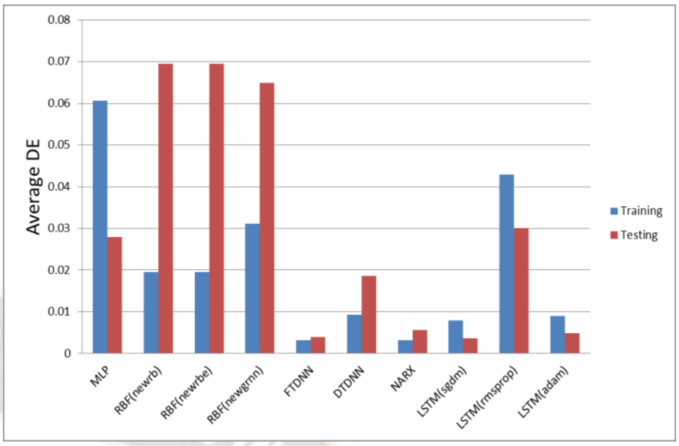


**Figure 4:** Analysis of prediction performance considering DE using mobility model dataset

Figure 6.4 depicts the performance analysis of mobility predictor models considering geographical coordinates average distance error (DE) with training and testing sets using mobility model dataset. For training sets, the DE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.060640, 0.057004, 0.057005, 0.650551, 0.009981, 0.645813, 0.009639, 0.012343, 0.028218, 0.013690. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.027887, 0.033264, 0.033265, 0.035596, 0.010657, 0.030702, 0.018323, 0.004675, 0.017084, 0.007684.

*(e). Based on regression (R)*

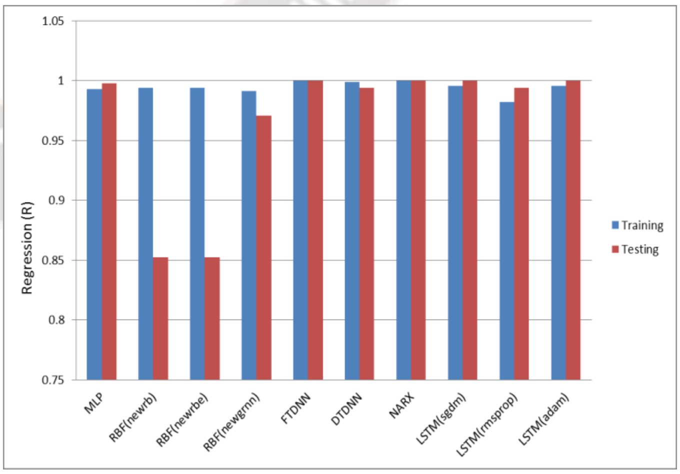


**Figure 5:** Analysis of prediction performance considering regression R using mobility model dataset

Figure 6.5 depicts the performance analysis of mobility predictor models considering regression R with training and

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testing sets using mobility model dataset. For training sets, the regression R values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.98462, 0.98615, 0.98615, 0.9858, 0.99962, 0.99786, 0.99967, 0.99887, 0.99659, 0.99881. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.99406, 0.99204, 0.99204, 0.99071, 0.99924, 0.99465, 0.99915, 0.99983, 0.99801, 0.99966.

The discussion above demonstrates that dynamic neural networks perform better than static neural network models because they incorporate time delay, which makes it easier to memorize the positions of the nodes in a time sequence and gives the prior knowledge required to predict the positions of the nodes in the future. NARX and FTDNN had the lowest error scores in the training phase. However, in the testing phase, the SGDM-based LSTM and Adam-based LSTM both scored lower in terms of inaccuracy. We chose the generalization error or testing error as the criterion for selecting the ANN predictor model since training with a very small mistake can impair the predictor models' capacity to generalize.

*5.2. Mobility prediction analysis using real-world dataset*

It is elaborated on the performance analysis of mobility prediction models using a real-world dataset with performance metrics for MSE, RMSE, MAE, and DE. The network regression R program's most recent training and testing sets are covered in more depth in this section.

*(a). Based on Mean Square Error (MSE)*

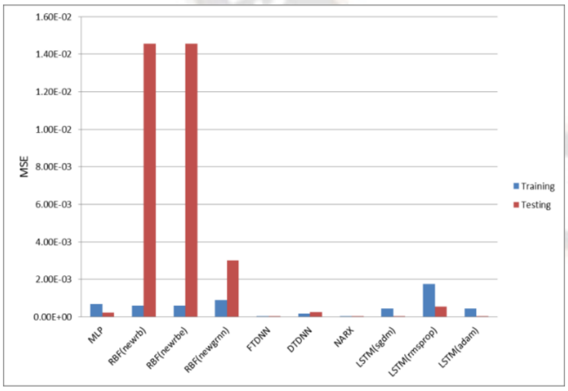


**Figure 6:** Analysis of prediction performance considering MSE using real-world dataset

Figure 6.6 depicts the performance analysis of mobility predictor models considering MSE with training and testing sets using real-world dataset. For training sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 6.71E-04, 5.89E-04, 5.89E-04, 8.87E-04, 2.16E-05, 1.82E-04, 2.03E-05, 4.35E-04, 0.001743, 4.43E-04. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 2.30E-04, 1.64E-02, 1.64E-02, 3.00E-03, 9.81E-06, 2.58E-04, 2.22E-05, 9.66E-06, 5.48E-04, 1.41E-05.

*(b). Based on Root Mean Square Error (RMSE)*

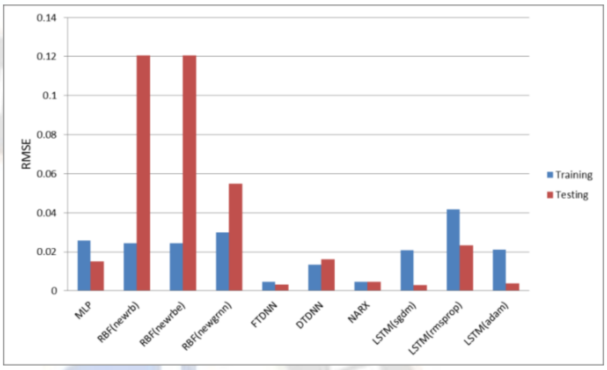


**Figure 7:** Analysis of prediction performance considering RMSE using real-world dataset

Figure 6.7 depicts the performance analysis of mobility predictor models considering RMSE with training and testing sets using real-world dataset. For training sets, the RMSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.025895, 0.024274, 0.024274, 0.029779, 0.004644, 0.013475, 0.004510, 0.020865, 0.041752, 0.021045. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.015171, 0.120660, 0.120660, 0.054794, 0.003131, 0.016068, 0.004711, 0.003108, 0.023414, 0.003750.

*(c). Based on Mean Absolute Error (MAE)*

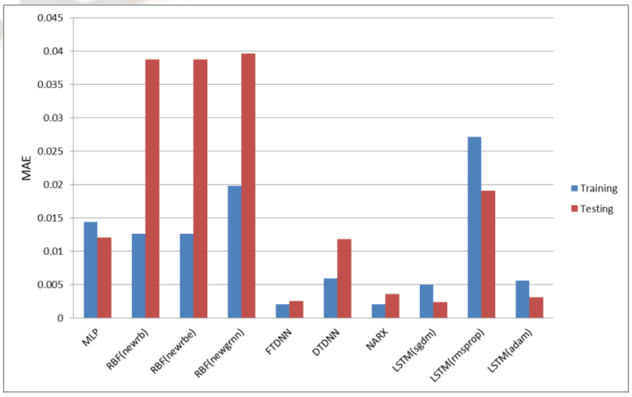


**Figure 8:** Analysis of prediction performance considering MAE using real-world dataset

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Figure 6.8 depicts the performance analysis of mobility predictor models considering MAE with training and testing sets using real-world dataset. For training sets, the MAE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are , 0.014353, 0.012572, 0.012572, 0.019803, 0.002069, 0.005905, 0.002073, 0.004924, 0.027080, 0.005568. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.012044, 0.038733, 0.038733, 0.039594, 0.002557, 0.011770, 0.003600, 0.002353, 0.019063, 0.003046.

*(d). Based on geographical coordinates (average) distance error (DE)*

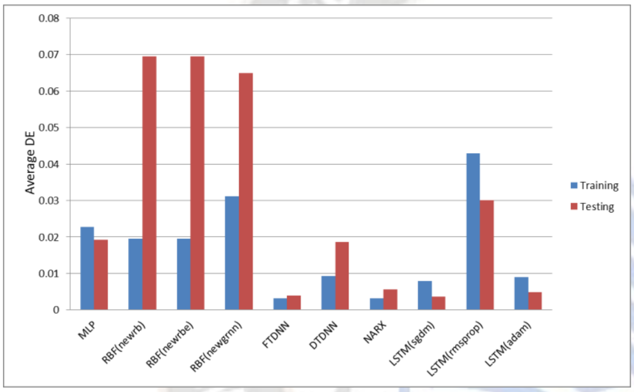


**Figure 9:** Analysis of prediction performance considering DE using real-world dataset

Figure 6.9 depicts the performance analysis of mobility predictor models considering geographical coordinates average distance error (DE) with training and testing sets using real-world dataset. For training sets, the DE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.022776, 0.019523, 0.019523, 0.031129, 0.003265, 0.009252, 0.003259, 0.007982, 0.042945, 0.008941. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.019204, 0.069447, 0.069447, 0.064844, 0.003932, 0.018583, 0.005684, 0.003682, 0.030033, 0.004837.

*(e). Based on regression (R)*

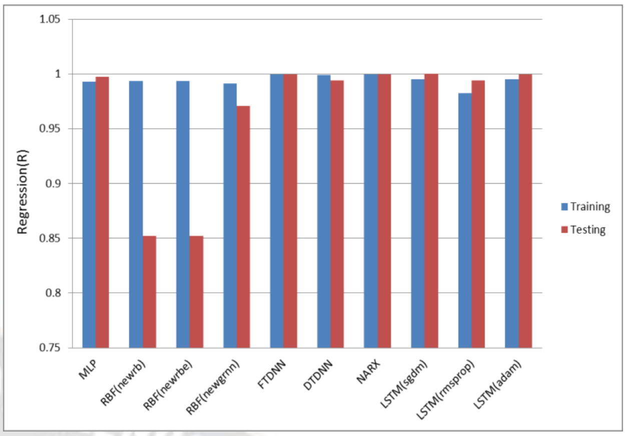


**Figure 10:** Analysis of prediction performance considering regression R using real-world dataset

Fiure 6.10 depicts the performance analysis of mobility predictor models considering regression R with training and testing sets using real-world dataset. For training sets, the regression R values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.9929, 0.9938, 0.9938, 0.9911, 0.9998, 0.9989, 0.9998, 0.9954, 0.9822, 0.9953. For testing sets, the MSE values computed by MLP, newrb based RBF, newrbe based RBF, newgrnn based RBF, FTDNN, DTDNN, NARX, sgdm based LSTM, rmsprop based LSTM and adam based LSTM are 0.9975, 0.8520, 0.8520, 0.9706, 0.9997, 0.9941, 0.9997, 0.9999, 0.9939, 0.9999.

The discussion above demonstrates that dynamic neural networks perform better than static neural network models because they incorporate time delay, which makes it easier to memorize the positions of the nodes in a time sequence and gives the prior knowledge required to predict the positions of the nodes in the future. NARX and FTDNN had the lowest error scores in the training phase. However, in the testing phase, the SGDM-based LSTM, followed by FTDNN and Adam-based LSTM, scored with the least amount of error. We chose the generalization error or testing error as the criterion for selecting the ANN predictor model since training with a very small mistake can impair the predictor models' capacity to generalize.

Tables 6.1–6.4 provide a rundown of all the ANNs' results in summary form. The performance of the ANN is better if MSE, RMSE, MAE, and average DE values are lower, as previously indicated in figures. The correlation between outputs and targets is represented by the R value, and a value closer to 1 indicates almost identical outputs and targets.

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**TABLE 2** gives an overview of the data collected from all ANN training sets using the mobility model dataset.

| ANN Model | Training | | | | |
|---|---|---|---|---|---|
| | MSE | RMSE | MAE | DE | R |
| MLP | 0.002438171 | 0.049377843 | 0.038642567 | 0.06064 | 0.98462 |
| RBF(newrb) | 0.002196954 | 0.046871671 | 0.036710793 | 0.057 | 0.98615 |
| RBF(newrbe) | 0.002196968 | 0.046871824 | 0.036710855 | 0.05701 | 0.98615 |
| RBF(newgrnn) | 0.00227957 | 0.04774484 | 0.037117589 | 0.65055 | 0.9858 |
| FTDNN | 7.08E-05 | 0.008416751 | 0.006329636 | 0.00998 | 0.99962 |
| DTDNN | 4.24E-04 | 0.020601097 | 0.015717122 | 0.64581 | 0.99786 |
| NARX | **6.59E-05** | **0.008116338** | **0.006150429** | **0.00964** | **0.99967** |
| LSTM(sgdm) | 1.80E-04 | 0.013416553 | 0.007946868 | 0.01234 | 0.99887 |
| LSTM(rmsprop) | 5.58E-04 | 0.023627162 | 0.018243565 | 0.02822 | 0.99659 |
| LSTM(adam) | 1.90E-04 | 0.013795211 | 0.008688004 | 0.01369 | 0.99881 |

**TABLE 3** gives an overview of the data collected from all ANN testing sets using the mobility model dataset.

| ANN Model | Testing | | | | |
|---|---|---|---|---|---|
| | MSE | RMSE | MAE | DE | R |
| MLP | 5.29E-04 | 0.02300007 | 0.017904173 | 0.02789 | 0.99406 |
| RBF(newrb) | 7.26E-04 | 0.026952782 | 0.021277809 | 0.03326 | 0.99204 |
| RBF(newrbe) | 7.26E-04 | 0.026953198 | 0.021277856 | 0.03327 | 0.99204 |
| RBF(newgrnn) | 8.90E-04 | 0.029829419 | 0.023458351 | 0.0356 | 0.99071 |
| FTDNN | 7.21E-05 | 0.008491719 | 0.007060643 | 0.01066 | 0.99924 |
| DTDNN | 6.10E-04 | 0.024701863 | 0.019952364 | 0.0307 | 0.99465 |
| NARX | 2.10E-04 | 0.014496862 | 0.011921323 | 0.01832 | 0.99915 |
| LSTM(sgdm) | **1.56E-05** | **0.003952015** | **0.002969817** | **0.00468** | **0.99983** |
| LSTM(rmsprop) | 1.90E-04 | 0.013779761 | 0.010819327 | 0.01708 | 0.99801 |
| LSTM(adam) | 3.57E-05 | 0.005978718 | 0.004937329 | 0.00768 | 0.99966 |

**TABLE 4** gives an overview of the data collected from all ANN training sets using the real-world dataset.

| ANN Model | Training | | | | |
|---|---|---|---|---|---|
| | MSE | RMSE | MAE | DE | R |
| MLP | 6.71E-04 | 0.02589503 | 0.01435393 | 0.0228 | 0.99292 |
| RBF(newrb) | 5.89E-04 | 0.02427437 | 0.01257211 | 0.0195 | 0.99378 |
| RBF(newrbe) | 5.89E-04 | 0.02427419 | 0.01257221 | 0.0195 | 0.99378 |
| RBF(newgrnn) | 8.87E-04 | 0.02977966 | 0.0198036 | 0.0311 | 0.9911 |
| FTDNN | 2.16E-05 | 0.0046448 | 0.00206971 | 0.0033 | 0.99979 |
| DTDNN | 1.82E-04 | 0.01347544 | 0.00590513 | 0.0093 | 0.99892 |
| NARX | **2.03E-05** | **0.00451071** | **0.00207385** | **0.0033** | **0.99981** |
| LSTM(sgdm) | 4.35E-04 | 0.02086543 | 0.00492462 | 0.008 | 0.99542 |
| LSTM(rmsprop) | 0.00174325 | 0.04175228 | 0.02708037 | 0.0429 | 0.98223 |
| LSTM(adam) | 4.43E-04 | 0.02104597 | 0.0055686 | 0.0089 | 0.99534 |

**TABLE 5** gives an overview of the data collected from all ANN testing sets using the real-world dataset.

| ANN Model | Testing | | | | |
|---|---|---|---|---|---|
| | MSE | RMSE | MAE | DE | R |
| MLP | 2.30E-04 | 0.01517148 | 0.01204494 | 0.0192 | 0.99748 |
| RBF(newrb) | 1.46E-02 | 0.12066016 | 0.0387333 | 0.0694 | 0.85199 |
| RBF(newrbe) | 1.46E-02 | 0.12066039 | 0.03873353 | 0.0694 | 0.85199 |
| RBF(newgrnn) | 3.00E-03 | 0.05479437 | 0.03959483 | 0.0648 | 0.97062 |
| FTDNN | 9.81E-06 | 0.00313171 | 0.00255713 | 0.0039 | 0.99972 |
| DTDNN | 2.58E-04 | 0.01606865 | 0.01177005 | 0.0186 | 0.99409 |
| NARX | 2.22E-05 | 0.00471199 | 0.00360044 | 0.0057 | 0.99966 |
| LSTM(sgdm) | **9.66E-06** | **0.00310838** | **0.00235336** | **0.0037** | **0.9999** |
| LSTM(rmsprop) | 5.48E-04 | 0.02341406 | 0.01906307 | 0.03 | 0.99386 |
| LSTM(adam) | 1.41E-05 | 0.0037506 | 0.0030469 | 0.0048 | 0.99988 |

## VI. SUMMARY

The mobility model and the real-world dataset are both taken into account in this analysis part. Both the training and testing sets are taken into account while doing the analysis. Using MSE, RMSE, MAE, and DE parameters, five performance metrics are used to validate the performance's effectiveness. For both training and testing sets, predictor models and network regressions R are also contrasted. According to the analysis, the predictor model NARX performed better than other predictor models on datasets from the mobility model and the real world, with minimal MSE values of 6.59E-05 and 2.03E-05, minimal RMSE values of 0.008116 and 0.004511, minimal MAE values of 0.00615 and 0.00207, minimal DE values of 0.00964 and 0.00326 and maximal regression values of 0.99967 and 0.99981, respectively. Similarly, the sgdm-based LSTM outperformed other predictor models on both datasets: the minimal MSE values of 1.56E-05 and 9.66E-06, the minimal RMSE values of 0.003952 and 0.003108, the minimal MAE values of 0.00297 and 0.002353, the minimal DE values of 0.004675 and 0.003682, and the maximal regression values of 0.99983 and 0.9999, respectively, of the testing sets. Thus, it is noted that the predictor model, a SGDM-based LSTM, reveals effective performance in mobility prediction. It is evident from the data that the dynamic neural network outperformed the static neural network.

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