

Time-Series Prediction for Sensing in Smart Greenhouses

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Abstract — Monitoring the climate is one of the most important and challenging practices by which to obtain optimum crop production in a greenhouse. In a smart greenhouse, a wireless sensor network (WSN) can be used to monitor the microclimate. Constant monitoring and sensing can result in excessive energy consumption. Prediction of the microclimate can be used to control the operation of sensors and hence lower the energy consumed by sensor nodes. We develop a Long Short-Term Memory (LSTM) based on time series for the prediction of the maximum, minimum, and mean values of the air temperature, relative humidity, pressure, wind, and dew point. Microclimate data inside and Macroclimate data outside the greenhouse are collected daily and used for the analysis of the best-fitting LSTM model. After determining the network structure and parameters, the network is then trained. The statistical criteria for measuring the network performance are the Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). A comparison is made between the measured and predicted values of temperature, relative humidity, pressure, dew point and wind. Results indicate the effectiveness of the predictive model performance LSTM in predicting the microclimate. Statistical analysis of the RMSE and MAE results demonstrate the prediction accuracy of our proposed LSTM model.

Keywords—Machine Learning, Long Short-Term Memory, Wireless Sensor Networks, Root mean Square Error, Mean Absolute Error, Microclimate, Greenhouse.

I. INTRODUCTION

Wireless sensor networks (WSN) are groups of sensors node that have multi-function and can be deployed in large scale to sense, collect, process and then transmit data between these nodes [1-3]. One of the applications of WSN is in large scale production greenhouses, as shown in Figure 1. However, the number of data transitions between common nodes and sink nodes in this specific environment will increase significantly along with network size, which can cause data congestion, a high rate of sensory data loss, and a low signal-noise ratio [4-5]. In order to prolong the lifetime of the network, it is necessary to control the duty cycles of sensors. There are many methods that still using redundant and periodic sensory data which based on historical data, that

usually will result with low prediction accuracy [6-8]. Data prediction helps improve data quality and reduces unnecessary data transmission. However, the prediction of the microclimate in a greenhouse is a challenging task for researchers. Temperature, humidity, dew point, pressure, and wind have a close relationship with, and a direct influence on, smart greenhouse crop production. The prediction of microclimates is useful in the thermal analysis of a greenhouse with respect to enabling the cooling and heating load calculation. The prediction and control of all the microclimate parameters will help reduce plant stress, decrease the growth of fungus, decrease the number of pests, and foster an appropriate environment for growing crops. A smart greenhouse microclimate is a complex nonlinear system that provides a good environment for growing. In order to do so, a smart greenhouse requires technologies and tools to process data at a reasonable cost and to translate that data into better decisions and actions [9]. Thus, it is important to accurately predict a greenhouse microclimate for environmental control and crop management. When the weather background and the composition of the greenhouse components of the system are determined, the system's unique agricultural microclimate characteristics will be relatively stable, which is conducive to prediction.

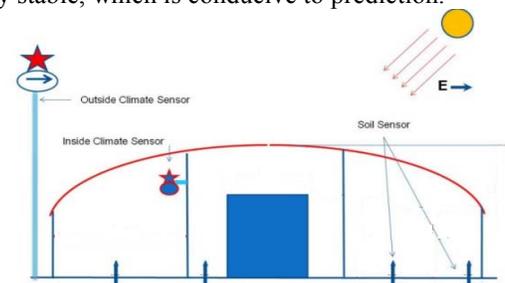


Fig. 1. Wireless Sensor Network in a Smart Greenhouse

Because of the complexity of the factors involved, the slow time variation, and the non-linearity of the smart greenhouse microclimate, it is difficult to build a precise mathematical model. The known and current greenhouse microclimate modelling has the following three approaches: computational fluid dynamics model method, the mechanism by design modelling method, and the system identification method. These methods have several limitations and unknown parameters; they also require expensive instruments and tests [10-14]. Our proposed model overcomes these drawbacks by

using LSTM model with data collected from sensors network to control the climate inside the greenhouse. The model has better prediction with high accuracy that stabilise the atmosphere inside the greenhouse to have good quality production. The model can also be used to control the duty cycles of the sensors which will decrease the energy consumption and cost production.

The reminder of this paper is organized as follow. Section II describes the related work. Section III describe the wireless sensor network monitoring in greenhouse. Section IV introduces our proposed work used throughout this paper. Section V describes the building model with two phases, training phase and prediction phase. Section VI shows the evaluation metrics to the model with the results. Finally, the last section presents our conclusions.

II. RELATED WORKS

In recent years, machine learning and deep learning have developed rapidly and have significantly contributed to the advancement of prediction models. These models were shown to enhance the quality, accuracy, generalization ability, and robustness of the conventional time series prediction tools. Many models based on regression and the neural network have been built [15,16]. Recurrent Neural Network (RNN) has many applications in speech recognition, machine translation, and time-series data prediction due to its memory capability. The Long Short-Term Memory (LSTM) neural network is based on the development of RNN. Since, LSTM based on time series of connecting previous information to the present task and having huge memory. LSTM is able to remember information for periods of time. This makes LSTM a good candidate model to forecast the greenhouse microclimate. LSTM performs well when processing long-term dependencies of time series data and predicting long-interval events as in [17]. With the existence of the Internet of Things (IoT) and cloud services, a large amount of environmental data can be saved and accessed, which will facilitate LSTM model accuracy.

In [20], the authors proposed a predictive solution for disaster monitoring using a neural network – based Multivariate Correspondence Analysis (MCA-NN). The MCA-NN model aims to improve the detection results by combining features from multivariate shallow learning models as described in [20]. Others use Cellular Neural Networks (CNN) to monitor desertification. Authors in [18] used a cellular neural network as a means to predict the trend of land desertification from 2000 to 2011; the experiment showed that the CNN model is better when they used an exponential smoothing model first before the prediction. Also, the authors in [19] proposed a method based on the artificial neural network to predict irrigation requirements. The paper uses the multi-layer perceptron model to extract the climate information retrieved from the public weather forecast to predict current crop evapotranspiration. In [24], the authors build an autoregressive neural network model for the seasonal weather, to map the nonlinear relationship of the data collected to get reliable prediction results.

III. PROPOSED FRAMEWORK

In our proposed model, we noted the drawbacks of the previous works such as: not including all the weather forecasts, not counting the prediction of the maximum, minimum, and average of all the microclimates, which helps establish boundaries for the prediction of weather values to enhance accuracy. Our proposed framework is based on the prediction model which will control the condition inside the smart greenhouse to have a stable microclimate. The proposed framework is shown in Figure 2.

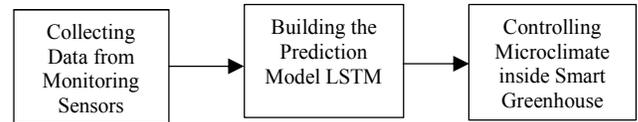


Fig.2. Proposed Framework

By knowing the duration of the crop growth, we can control the greenhouse environment to speed up the growth of the plants and to protect them from diseases. Predicting greenhouse parameters will allow growers to reach the optimal parameters and control the climate inside greenhouse. Thus, decreasing and stopping any fungal or pest infestation in the crop and decreasing the consumption of the sensor’s energy. Inside our case study greenhouse, there were wireless sensor networks located in many areas to measure temperature, humidity, and air pressure. These measurements are collected and used in RNN with long memory (LSTM) for prediction.

Based on our predictions, and to increase the accuracy of our proposed model, we apply two different gradient descent optimization algorithms Adam [23] and the Stochastic Gradient Descent (SGD) [25]. After prediction, we can change the temperature inside the greenhouse to the desired level and control the temperature by having the actuator open the window, switch on the heater or switch on the fan. Our model was tested on different datasets collected (hourly, daily, weekly) from wireless sensor monitoring. Additionally, our model can predict distinct lengths of time (seven days, 30 days, 90 days).

IV. A PREDICTION APPROACH

In this section, we discuss our novel solution for predicting the microclimate inside a greenhouse.

A. Prelimanries

Let P_i^t denote the microclimate i at t^{th} time. Let $\{F_i^t \dots F_n^t\}$ be the climate features. Given a tuple (P,F), our goal is to predict $P_i^{t+1}, P_i^{t+2}, \dots, P_n^{t+m}$, where m is the number of days for which prediction is required.

B. Proposed Solution

Figure 3 represents a three-step process described below.

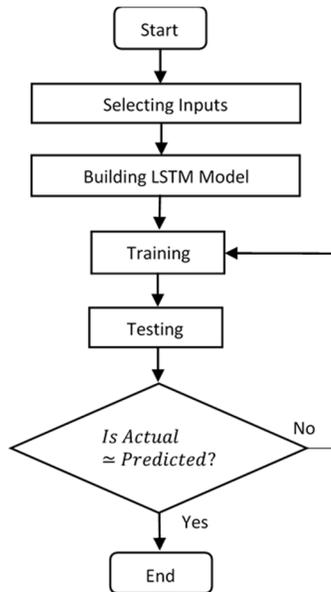


Fig. 3. Flow Chart for the Proposed Model

1. Data Collection

We utilize a data set collected by many types of wireless sensors have been installed inside and outside a greenhouse in Surrey, British Columbia to monitor the macroclimate [26]. Temperature, humidity, pressure, dew point, and wind data were recorded and analyzed with the help from Weather Underground, a community of volunteers reporting data taken from specific weather sensors, located in British Columbia. This data has been collected for five years from January 1, 2015 to December 30, 2019, on an hourly, daily, and weekly basis for each month throughout those five years. From that dataset we collected the maximum, minimum, and average data for all five indicators.

In this study, the daily microclimate data from the interior of the greenhouse and the macroclimate data, from outside the greenhouse, for the years 2015 to 2019 were used to train and test our proposed model for weather prediction for one week, 30 days and 90 days. The inputs for the model were the maximum, minimum and mean temperature (T) and relative humidity (RH) of the greenhouse, the outside average wind speed (WS), the pressure (P), and the dew point (DW). The output weather predictions were for one week, 30 days and 90 days in the future. The sample of the microclimate data is shown in Figure 4.

2. Training and Fitting the LSTM Model

After collecting data from sensors, we need to prepare the data set to be fed to the model using cleaning process. No missing values in a total of 1826 records, data set has to be numerical value, apply scaling and then normalization on all data set. The prepared dataset is divided into training and testing sets; these sets are then split into input and output variables. In LSTM the input changed to be in 3D format [features, samples, timesteps]. For purposes of predicting all the weather conditions, we will define the LSTM with 50 neurons in the first hidden layer and with 15 neurons in the output layer. The input shape will be a one-time step with 15 features.

We use the Mean Absolute Error (MAE) loss function and the optimization function Adam version of the stochastic gradient descent. The model will be fit for 1500 training epochs with different batch sizes and activation function (Relu). We can forecast for all the test dataset after fitting the model. We will combine the forecast with the test dataset and invert the scaling. Calculating the error score for the model by using original scale of forecasts and actual values. In this case, we calculate the MAE and Mean Square Error (MSE).

The LSTM model with two different gradient descent optimization algorithms is tested, and the results compared by calculating the Root Mean Square Error (RMSE). The best-suited model is selected based on the minimized values of MSE and MAE and used to measure the performance of the model.

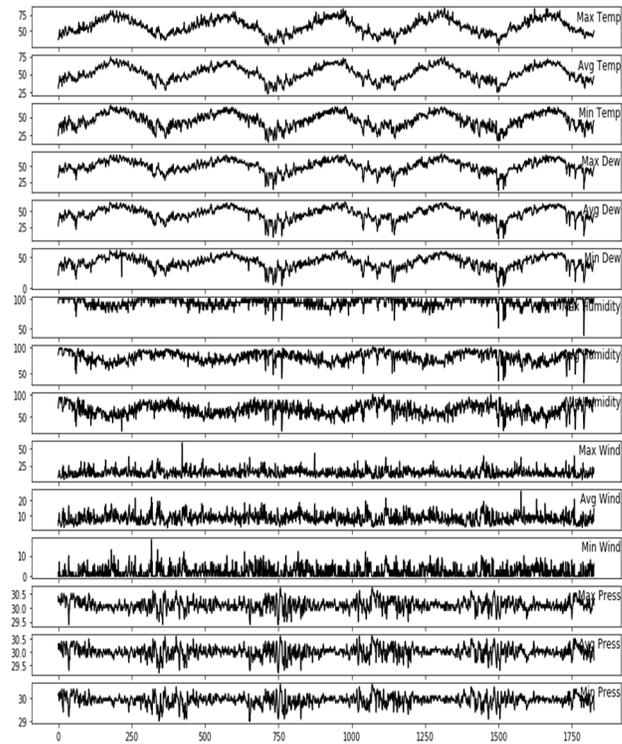


Fig.4: Weather Microclimate

3. Long Short-Term Model

There are two phases of the LSTM model: the training phase and the prediction phase.

a) Training Phase

The LSTM training model, shown in Figure 5, is used to predict the microclimate inside a greenhouse. Our LSTM model has three types of layers: an input layer, a hidden layer, and a dense layer. The input layer has 50 neurons and is used to provide input to the LSTM model. The input to the LSTM model is a vector containing the current (hour, day, or week) for the weather forecast data. This feature vector is denoted by x in the diagram, where x_n denotes the feature vector at time t . Our model has 16 hidden layers. The output of the LSTM model at time t is an initial parameter vector which is also an input for the model for time $t+1$. The hidden units are

internally connected, where output h_0 of LSTM at time t is the input of the next hidden unit. The hidden layer is used to adjust the weights assigned to the initial parameters based on the gradient descent difference. The output of the LSTM model at time t is also the input for the model for time $t+1$. This is because the LSTM behavior for that next hour's, day's, or week's output is dependent on the previous hour's, day's, or week's output. The last layer is the dense layer. The output of all units in the hidden layer h_i is connected to a dense layer whose output p_i has 15 units, which represents each microclimate forecast. These predicted values are then compared with the actual weather forecast's value at that time.

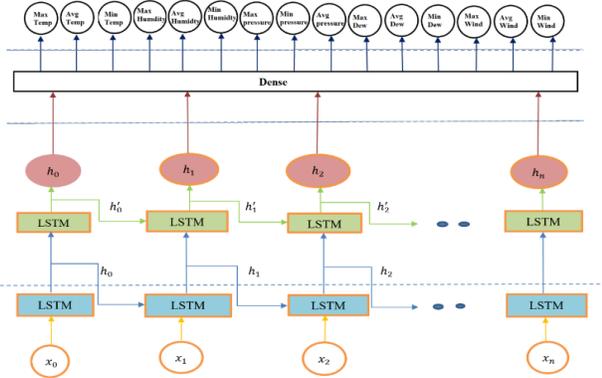


Fig. 5. LSTM Training Model with Input, Hidden, and Dense Layers

b. Prediction Phase

In the prediction phase, we use the trained LSTM model to predict the microclimate forecast for the next seven days, 30 days, and 90 days. The feature vector at time t is the input to the trained LSTM model that predicts the microclimate for the number of days, passed as an argument in the function. The next day's predicted values are appended with the corresponding day's weather forecast data to predict the next day's microclimate. The whole function is recursively called n times, where n is the number of days for which prediction is required. Because we are predicting next n number of days microclimate, instead of training a separate LSTM model for different values of n , one model is trained to predict the next day's values. That next day predicted values are extrapolated for the next day's prediction, as shown in Figure 6.

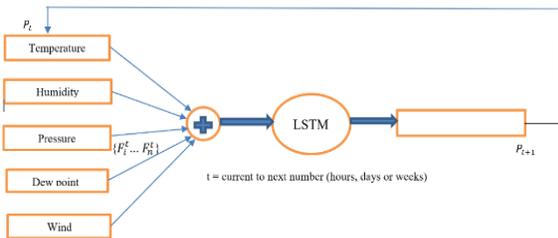


Fig. 6. LSTM Prediction Model

V. PERFORMANCE EVALUATION

The data is split into training, testing and validation. To assess the performance of proposed model, we compare the results of the training data and validation data in loss function. We used three loss functions to measure how accurately our model

can predict the expected outcome. The loss function is a measure of how well our model did at predicting the outcome. A high value for the loss means lower performance. A low value for the loss means our model performed very well. The three loss functions are explained below.

1. Evaluation Metrics

Three loss functions, MAE, MSE and RMSE, per Equations 1, 2 and 3, respectively. RMSE is the difference between the microclimate weather values predicted by a model and the values observed. Because the model is trained on past data, we report the RMSE for future microclimate weather prediction values. In Equations 1-3, n represents the test sample size. The MAE and MSE results are shown in Figure 7 and Figure 8, respectively. Hereinafter, we use MAE in our results. Because MSE loss function square the error and it will take times to reach to the minimum, rather than MAE loss function is subtracting the error and will be faster to reach to the minimum.

$$MAE = \frac{1}{n} \sum_{i=1}^n |Predicted_i - Actual_i| \quad (1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (Predicted_i - Actual_i)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Predicted_i - Actual_i)^2} \quad (3)$$

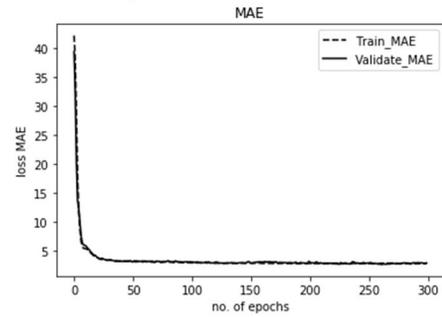


Fig. 7. MAE Result

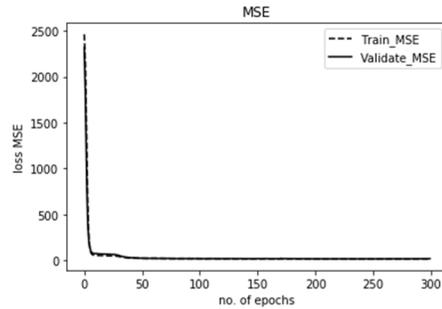


Fig. 8. MSE Result

2. Results and Discussion

Our proposed model is designed with multiple python packages including TensorFlow [21] and Keras [22] these are used to perform label encoding and scaling on our dataset, respectively. The LSTM model is used to predict the next number of days' temperature, humidity, pressure, dew point, and wind. There are multiple parameters (number of epochs, hidden layers, hidden neurons, etc.) on which the LSTM model works. Tuning all these parameters results in different RMSE values. We perform several experiments to find the optimal value of the parameters to achieve the least RMSE. There are two gradient descent optimization algorithms:

Adam [23] and Stochastic Gradient Descent (SGD) [25]. The advantage of the Adam algorithm over SGD is that global minima are achieved in fewer epochs. Using Adam algorithm is faster than SGD algorithm to find global minima with fewer epochs, as shown in Figure 9(a, b) and Figure 10(a, b), respectively.

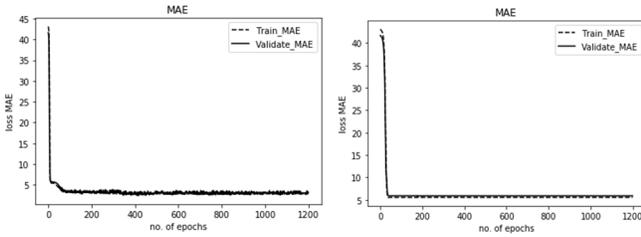


Figure 9.a: 50 Neurons, SGD

Figure 9.b: 5 Neurons, SGD

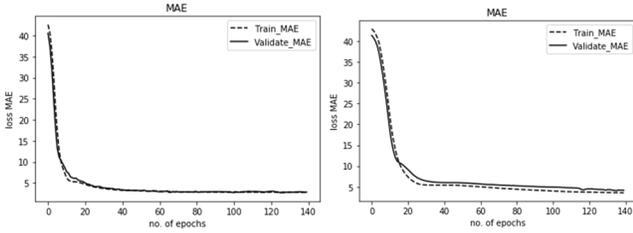


Figure 10.a: 50 Neurons, Adam

Figure 10.b: 5 Neurons, Adam

Figures 9 and 10 show the effect of which optimization algorithm are faster to reach global minima with fewer epochs when there is different input neuron. Also, in both Figures, the global minima are achieved with the least number of epochs when the number of neurons is higher. As the figures show, 50 neurons perform better than five neurons in terms of achieving global minima. In Figure 11b, the use of 50 neurons and the Adam algorithm achieved the global minima in fewer than 30 epochs, while in Figure 10b, the use of 50 neurons and the SGD algorithm achieved the global minima in 200 epochs.

We used the Adam algorithm with one hidden layer, 50 hidden units, and 150 epochs in our framework to obtain the global minima. We did not define the learning rate in the Adam algorithm since the algorithm already calculates the individual adaptive learning rate for each parameter.

The RMSE results for seven days, 30 days, and 90 days for all the atmospheres are shown in Figures 11, 12 and 13, respectively. Each figure represents the five features (temperature, relative humidity, pressure, dew point and wind) for the predicted and actual data. From the results, we can see that the proposed model can predict the future weather inside the greenhouse with a high level of accuracy and the three figures prediction accuracy were almost the same in all of them.

VI. CONCLUSIONS

In smart greenhouses, monitoring and controlling the microclimate parameters are critical for having high quality production of crops. In this paper, we use maximum, minimum, and average environmental data collected from wireless sensor nodes to improve the model prediction accuracy. LSTM with different optimization algorithms was applied to the training and testing of environmental data that

was collected over a five- year span. The prediction results shown for seven days, 30 days, and 90 days ahead were promising. The accuracy of the model performance, as evaluated by measurements of AME, MSE and RMSE, was high. The proposed model will significantly be useful in predicting and controlling the duty cycles of the sensors inside the greenhouse. This will lead to decreasing the energy consumption of the sensor network and the production cost.

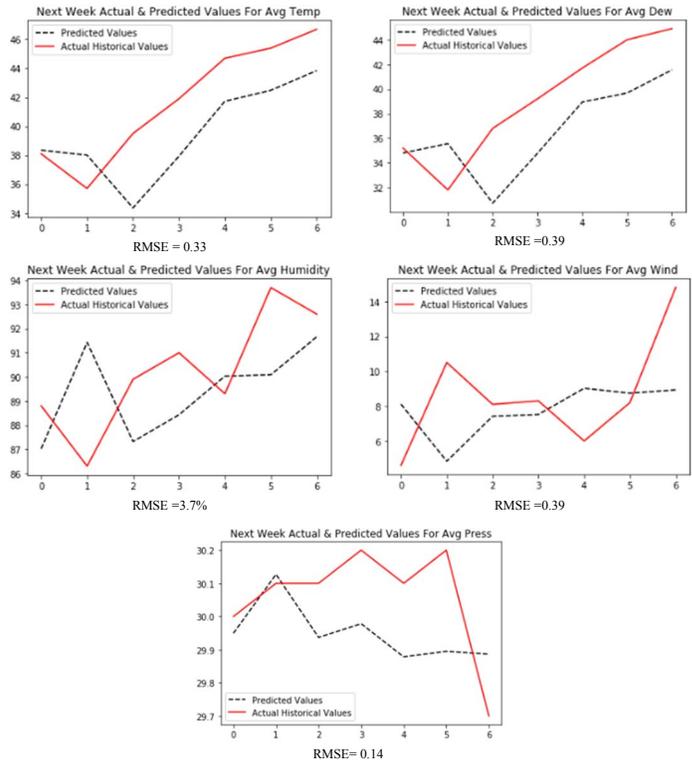


Fig. 11. Prediction for Seven Days Ahead

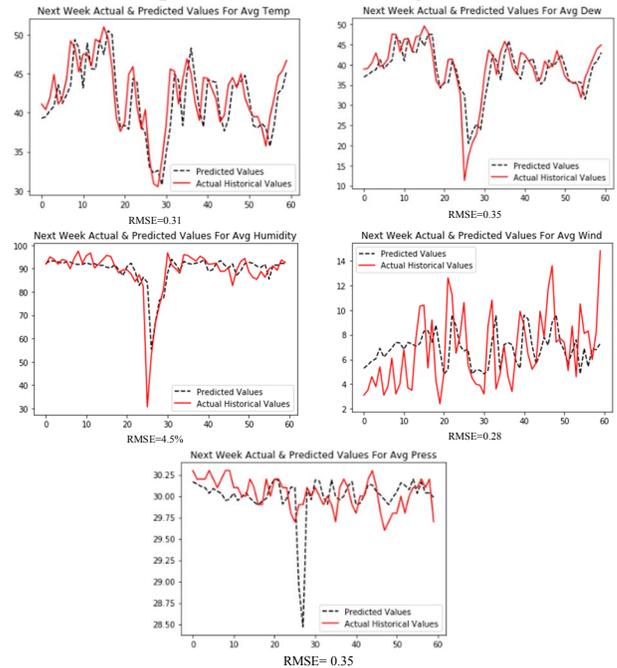


Fig. 12. Prediction for 30 Days Ahead

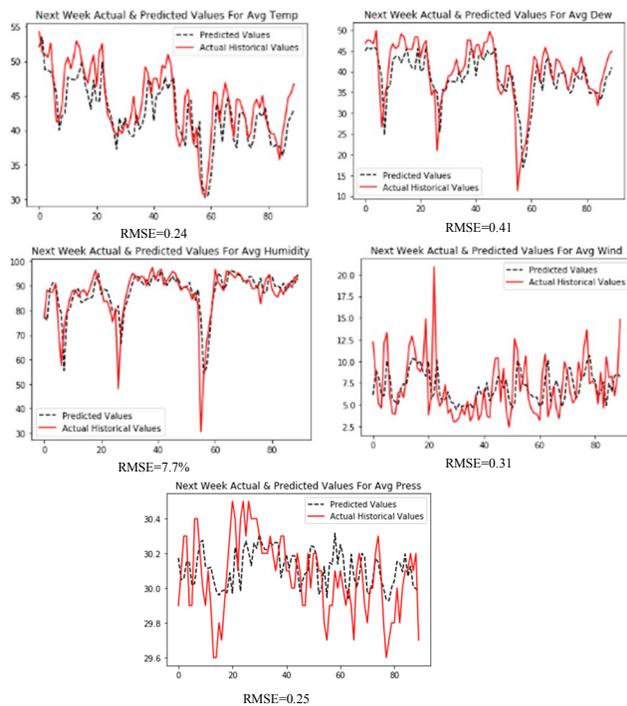


Fig. 13. Prediction for 90 Days Ahead

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