Wireless Sensor Network and Deep Learning For Prediction Greenhouse Environments

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***Abstract*—Greenhouses are anti-seasonal. Particularly in regions with adverse climate conditions. Controlling, monitoring and predicting a greenhouse is important to allow optimal growth condition for crops. However, testing the greenhouse for real atmosphere requires a lot of time, effort and money. The modeling and simulation approach is best suited to predict thereby improve the greenhouse environment. This paper presents a model for predicting environmental atmosphere for producing tomatoes in greenhouse. Several factor such as: air temperature, humidity, barometric pressure, and dew point are needed to be monitered . Since atmosphere pattern are complex and are a nonlinear system, the customary methods for prediction are inefficient and ineffective. Recurrent neural network (RNN) with long short-term memory are a solution. The proposed RNN evaluate the performance of the model by using different neurons, hidden layers and transfer functions to predict the environmental parameters of the greenhouse for an entire year ahead. By utilizing the Root Mean square error (RMSE) to evaluate the performance of the proposed model, results show our model has very low RMSE and time.**

***Index Terms*—wireless sensor network, greenhouse, recurrent neural network, Long short-term memory, root mean square error.**

I. Introduction

One of the important and challenging problems in greenhouse is to create and maintain an ideal environment for the specific crop. A well-controlled greenhouse will help maximize productivity. Thus, maintaining ideal environmental parameters inside the greenhouse according to the plant growth cycle is without question essential. Therefore, smart greenhouses have wireless sensor networks (WSNs) and actuators. WSNs sense the atmosphere in the greenhouses measuring humidity, temperature, pressure, carbon dioxide levels, etc. If any anomaly is detected the central base station sends a message to actuators to perform necessary actions such as activating the watering system, open greenhouse windows, apply pesticides and, reduce irrigation.

In addition, a proper understanding of the variations in greenhouse microclimate, in conjunction with the requirements of the specific crop at different stages of growth, need more attention. As tomato plants are sensitive to broad fluctuations in air temperatures, greenhouse cultivation in geographic regions with such climate conditions that are not adequately close to the base requirements will involve additional risks and production costs.

Solely depending on measurements taken from sensors is not enough for having healthy crops in greenhouse. Having a deep learning model for predicting the future atmospheric parameters will help in maintaining the best environment. For example knowing the humidity or temperature ahead will help to decrease the likelihood of fungus or any kind of pest that can harm the plants. Also, predicting environmental changes will help in case a sensor malfunctions, and saving the power consumption in the greenhouse. In addition, automated process will decrease the human interaction, and decrease the labor cost.

II. Related Works

Data prediction can be used in many applications including prediction in wireless sensor networks, traffic flow prediction, weather prediction, financial prediction, and predicting an emergency.

Weather prediction or early-warning models based on deep learning have become popular in recent years. Authors in [1] presented a neural network-based multivariate correspondence analysis model (MCA-NN) for natural disaster monitoring. The MCA-NN model aims to improve detection results by combining features from multivariate shallow learning models. Another author uses cellular neural networks to predict the degree of desertification. The Ruoqiang Basin is used as an example to predict the trend of land desertification from 2000 to 2011, the experiment shows that the cellular neural network model is better than others [2]. In [3] the author proposed a method based on artificial neural network to predict the recent irrigation requirement. The paper uses the multi-layer perceptron model to extract the climate information retrieved from the public weather forecast to predict the recent crop evapotranspiration. Also, the author of [4] proposed a multi-weather attribute model to predict weather based on nonlinear autoregressive neural networks.

There has been much research regarding modeling greenhouse control systems. Some research has focused on how to model and control the greenhouse model [5]. This research applied several methods, like physical modeling [6], autoregressive exogenous (ARX) modeling, and artificial neural network

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(ANN), to create plant models. They showed pros and cons of each modeling approach, but they did not consider building a model for predicting the climate inside the greenhouse nor did they consider the stages of crop life.

A greenhouse environment is considered a dynamic and complex system, with few models having been studied for growing tomatoes specifically up to now. In the literature TOMGRO and TOMSIM [7], [8], are considered as the main applicable dynamic growth models. Those models are dependent on physiological processes, and they represent biomass partitioning, crop growth, and yield as a function of several climate and physiological parameters. However, due to their limited application to practical settings, their complexity, the difficulty in estimating initial parameter values and the need for calibration and validation in every new environment, the adoption of these by growers uptake has been limited.

Therefore, we propose a prediction model using recurrent neural network with long short-term memory which will predict the weather and help to improve the environment inside the greenhouse.

III. Tomato plant growth

The optimum levels of microclimate for the best greenhouse cultivation of tomatoes depends on different growth stages and conditions. There are five stages for the tomato: germination and early growth with initial leaves took between 25-35 days, vegetative period between 20-25 days, flowering period 20 to 30 days, early fruiting period between 20 to 30 days, and mature fruiting period between 15 -20 days [9]. The exact period of days depends on the atmosphere inside the greenhouse. For most greenhouse tomatoes to reach maturity and ripeness is between 65 to 100 days. Shortening the production time can be done by changing the conditions inside the greenhouse. Depending on the maturity level of the cultivar. The growth stages of tomato are illustrated graphically in Fig. 1 , along with different fruit maturity and ripeness level. It should be noted that tomatoes are harvested only when they have reached the mature green stage (vine-ripe), just as they start to ripen.

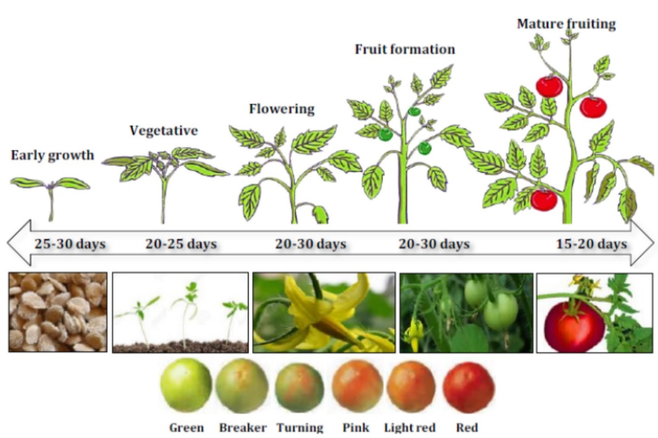


Fig. 1. Five growth stages for tomato plants

Temperature higher or lower than the optimal values affects different phases of growth and development of tomato. High temperatures cause the fruit to die because of improper transpiration, and can destroy the plant. Tomato plants are notably sensitive to above optimal air temperatures during the reproductive stage and may face a reduction in the percentage of fruit set, which triggers a significant yield decrease in commercial cultivation. On the other hand, decreasing temperature will effect respiration and photosynthesis, and cause hormone imbalance in the tomato plant. In addition, a very highly level of humidity in the greenhouse environment causes diseases and fungal pathogens to grow and spread rapidly infecting the plants. Pests also spread faster in high temperatures and humidity. Some of the diseases and physiological abnormalities associated with high humidity in greenhouse production include black spot, powdery mildew, leaf-edge burn and blossom-end rot of tomatoes. As well, plants evapotranspiration may be limited. Barometric pressure directly affects the water uptake by tomato plants and likewise the overall tomato fruit yield. Extremely high or low pressure values can result in leaf physiology disorders and the fruit to die.

IV. Greenhouse Frameworks

By knowing the duration of the tomato growth, we can control the greenhouse environment to speed up the growth of the plants and also 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 infestation to occur. Inside our case study greenhouse, there were wireless sensor networks located in many area to measure temperature, humidity and air pressure. These measurements are collected and used in recurrent neural network (RNN) with long short-term memory (LSTM) for prediction. After prediction, we can change the temperature inside the greenhouse to the desired degree and control the temperature by having the actuator open the window, switch on the heater or close the fan.

V. Wireless Sensor Network

Wireless sensor networks (WSNs) have been successfully used to monitor environmental conditions. WSN offers the basic infrastructure for communication among sensors that will provide information about temperature, humidity, carbon dioxide concentration [13]. WSN are communication networks among constrained devices (limited computational power, memory and energy). These networks are composed of a large number of sensor nodes, which are deployed inside the greenhouses. Every node has components for sensing, data processing, and communication. Wireless sensor network in greenhouse as shown in Fig. 2 .

VI. Recurrent Neural Network (RNN)

A neural network is a strong data modeling tool that is able to represent complex relationship between input and output. The inspiration for the development of neural network

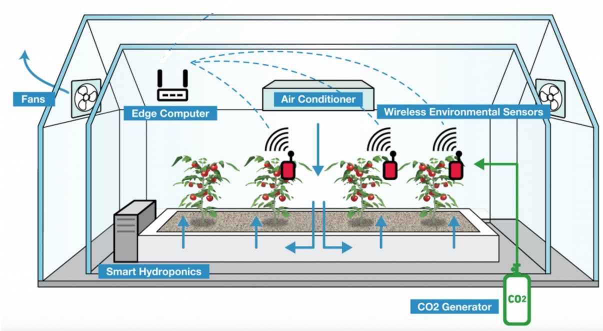


Fig. 2. Wireless sensor network inside the greenhouse

technology stemmed from the desire to implement an artificial system that could perform intelligent task similar to those performed by the human brain [10]. Neural network works like the human brain in the following way: neural network obtains knowledge through learning and information is stored within interneuron connection strengths which are known as synaptic weights. Neural network has the capability to characterize both linear and non-linear relationship directly from the data being modeled [11]. From a given set of data, neural network model is a structure that can be altered to create a mapping or relationship among the data set [12]. The network model is adjusted and then trained using a collection of data set which is generally referred as the training set. After successful training of the neural network it will be able to perform prediction, classification, estimation or simulation tasks on new data from the same or similar data sources.

A Recurrent Neural Network (RNN) is a type of artificial neural network well-suited to time series data. RNNs process a time series step-by-step, maintaining an internal state summarizing the information where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Unlike feedforward neural networks, RNNs can use an internal state (memory) to process sequences of inputs.

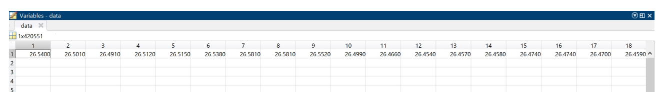
In this paper we use a specialized RNN that has layer of long short-term memory (LSTM) to forecast the values of future time steps of a sequence, by training a sequence-to-sequence regression LSTM network, where responses are the training sequences with values shifted by one time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step. Predicting the temperature, humidity and air pressure in the future.

VII. Long short-term memory (LSTM)

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can not only process single data points, but also entire sequences of data. These powers make LSTM the most commercial AI achievement [14]. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the exploding and vanishing gradient problems, can learn tasks that require memories of events that happened thousands or even millions of discrete time steps earlier.

VIII. The Weather Dataset

The temperature data set were collected from greenhouse in Germany, for observation every 10 minutes. These data collected between 2009 and 2016. This means that, for each hour will have 6 times observations of collecting data. Similarly, one day will contain 144 observations. In this work, we try to predict the temperature for 6 hours in the future. In order to make this prediction, we select five days of observations. This means we have a collection of last data 720 observations to train the model. But, for any drastic changes is not expected within the sixty minutes. So, only 120 observation will represents the history of the five days. For example of the temperature single step prediction model, the data point label is 12 hours into the future. which mean, to create the label for temperature, we need 72 observation is used. The temperature data is shown in Fig. 3 with size 420551 data set. The graph of the temperature and the time is shown in Fig. 4


Variables - data
data
1x420551

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	26.5400	26.5010	26.4910	26.5120	26.5150	26.5380	26.5810	26.5810	26.5520	26.4990	26.4660	26.4540	26.4570	26.4580	26.4740	26.4740	26.4700	26.4590
2																		
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Fig. 3. Temperature data set

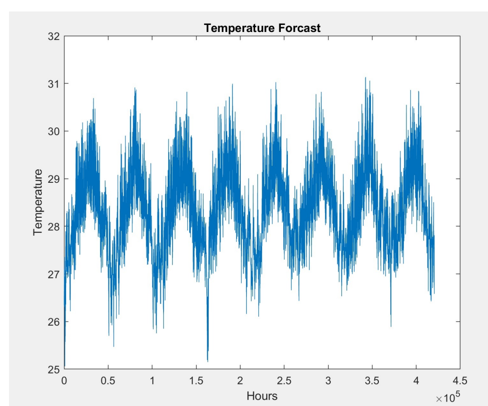

Fig. 4. Temperature versus time

IX. Training

After collecting dataset (temperature). Partition the training and test data. Train on the first 90% of the sequence and test on the last 10%. Normalize features before training a neural network. By subtracting the mean and dividing by the standard deviation of each feature. To forecast the values of future time steps of a sequence, specify the responses to be the training sequences with values shifted by one time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step. The predictors are the training sequences without the final time step. LSTM layer has 200 hidden units. Number of feature is one (temperature). We train for 250 epochs. To prevent the gradients from exploding, we set the gradient threshold to one with initial learn rate 0.005, and drop the learn rate after 125 epochs by multiplying by a factor of 0.2. Train the LSTM network. The root mean square error (RMSE) is used to measure the difference between values predicted by the model and values observed. RMSE is decreasing as shown in Fig. 5, which indicate that the prediction of temperature from the model is close to the observed temperature and the loss is equal to zero.

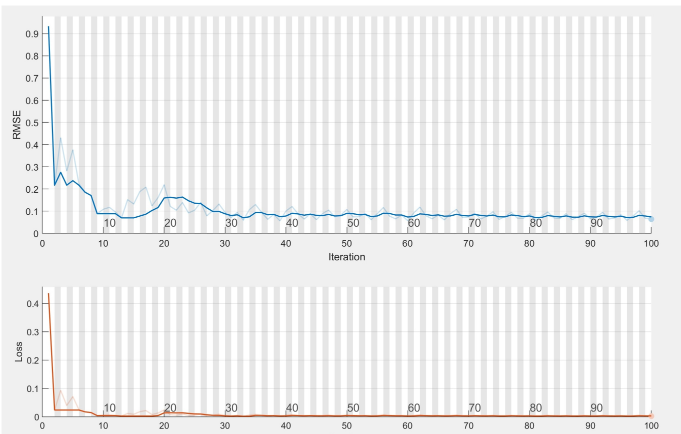

Fig. 5. RMSE and loss

X. Results

Now that the model is trained, The model is given the history of temperature feature over the past five days sampled every hour. Which means we have 120 data points. Our goal is to predict the temperature, for one day in the future as shown in Fig. 6.

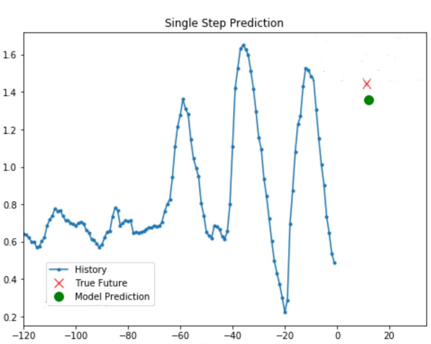

Fig. 6. Prediction temperature for one day in future

However, here, the model needs to learn to predict the temperature for the next 12 hours. Since an observation is taken every 10 minutes, the output is 72 predictions. For this task, the dataset needs to be prepared accordingly, thus the first step is just to create it again, but with a different target window. As shown in Fig. 7.

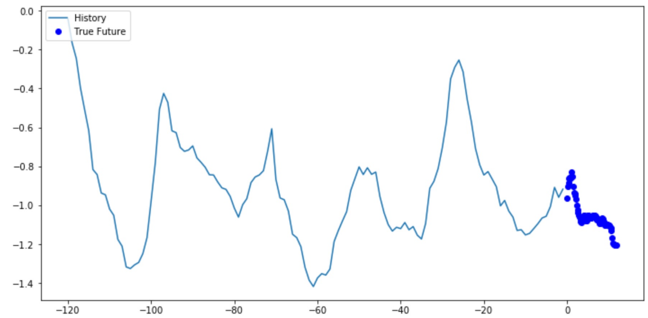

Fig. 7. Prediction temperature for 12 hours in future

The model now consists of two LSTM layers. Finally, since 72 predictions are made, the dense layer outputs 72 predictions. The training and validation loss shown in Fig. 8.

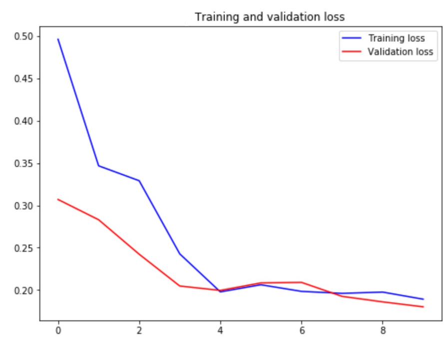

Fig. 8. Training and validation loss

The model is now able to predict the future temperature with high accuracy as shown in Fig. 9.

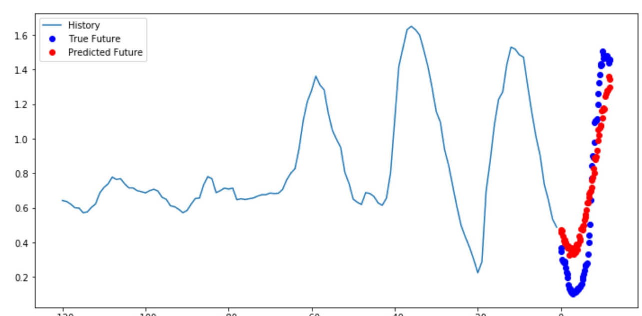

Fig. 9. Prediction the temperature

Compare the forecasted values with the test data. The predictions are more accurate Fig. 10 and RMSA =0.069 which is very small.

XI. Conclusions

Predicting and controlling the environmental parameters in greenhouse is one of the most important, and hard task

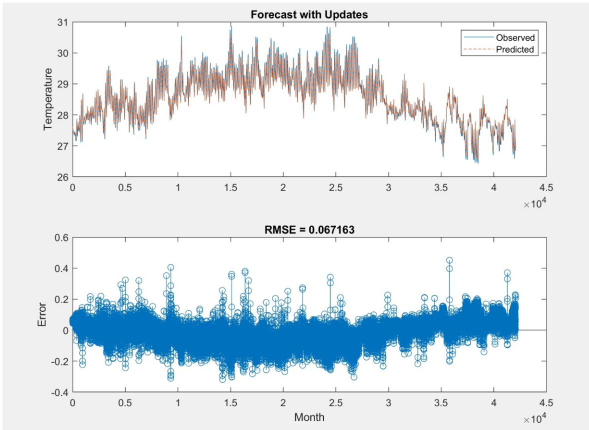

Fig. 10. Compare the forecasted value with test data

that need to be performed, with high level of accuracy to achieve optimal qualities and quantities of tomato crop production. This paper proposed prediction model for environmental greenhouse parameters specifically of tomato production. The model used recurrent neural network with long short-term memory. The model successfully predicted the future temperature with high accuracy and very low RMSE. For future work, we plan to expand the capability of the model to predict humidity, air pressure, and the growth of the plant as well.

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