Performance of Long Short-Term Memory Networks for Modeling the Response of Plant Growth to Nutrient Solution Temperature in Hydroponic

Galih Kusuma Aji [1,3,*], Kenji Hatou [2] and Tetsuo Morimoto [2]
[1]The United Graduate School of Agricultural Science
Ehime University, Matsuyama, 790-8566, Japan
[2] Faculty of Agriculture, Ehime University, Matsuyama, 790-8566, Japan
[3]Department of Bioresources Technology and Veterinary
Universitas Gadjah Mada, Yogyakarta, 55281, Indonesia
Email: galih.kusuma.aji@gmail.com*

Abstract

This study examines the development of an approach for modeling the response of plant growth to nutrient solution temperature in hydroponic cultivation in a dynamic system. Nutrient solution temperature is one of the essential manipulating factors for plant growth in hydroponic cultivation. Determining the optimal control strategy of nutrient solution temperature during cultivation could lead to maximize the growth of the plant. By identifying the process using a dynamic system, the optimal control strategy can be determined. However, developing a dynamic model of plant growth to nutrient solution temperature is not easy due to physiological behavior between them are quite complex and uncertain. We propose the long short-term memory (LSTM) networks to identify and develop a model of dynamic characteristics of plant growth as affected by the nutrient solution temperature. Chili pepper plants were used to obtain time-series data of plant growth, with five different types of dynamic nutrient solution temperature patterns for system identification. The results showed that the proposed LSTM model provides promising performance in predicting the response of plant growth to nutrient solution temperature in hydroponic cultivation.

Keywords: *Artificial neural networks, dynamic modeling, hydroponic, nutrient solution temperature, plant grow*

1. INTRODUCTION

Nutrient solution temperature in hydroponic cultivation is playing a significant role in promoting plant growth (He, 2016). Studies have suggested the correlation of nutrient solution temperature in many plant processes such as water absorption, water movement, and transpiration (Mortensen, 1982; Gosselin and Trudel, 1983; Ingram et al., 2015). The various nutrient solution temperature application also has been studied to control plant growth in hydroponic cultivation (Lay et al., 2002; Sakamoto and Suzuki, 2015a, 2015b; Sakamoto et al., 2016). However, the physiological status of the dynamic response of the plant to the effect of nutrient solution temperature has not been thoroughly investigated to control the plant production system. It is crucial because the physiological status of a plant during cultivation varies with time and is also significantly affected by the change in environmental factors.

In the modern greenhouse cultivation system, the growth promotion of plants is required to increase the yield and productivity of the plant production system. Determining the optimal control of environmental factors in a cultivation system is the key to maintain the growth of the plants. In order to search the optimal control strategy of environmental factors, an exact dynamic model of the process is necessary. The dynamic model is a useful method for the synthesis of the control system (Fasol and Jörgl, 1980).

In general, however, it is challenging to develop a dynamic model of plant growth to nutrient solution temperature due to eco-physiological behavior between them are quite complex and uncertain (Whittaker and Thieme, 1990). Therefore, in this study, we propose intelligent approaches that can deal with the complex system. Recently, intelligent technique, such as an artificial neural networks (ANNs), has been extensively developed. In agriculture, the ANNs technique has been rapidly applied to the plant production system (Morimoto and Hashimoto, 2000; Yumeina et al., 2017). This technique has known as a useful tool for dealing with really complex problems to which conventional mathematical approaches cannot be applied. ANNs is used for the dynamic model building of complex and fuzzy systems because it can well acquire the essential dynamics with its own high learning capability (Rumelhart et al., 2013). Hence, the intelligent technique mentioned above can be useful to identify and construct a model of the dynamic response of plant growth to nutrient solution temperature.

This study aims to examine the development of a dynamic model using long short-term memory (LSTM) networks to predict the future behavior of dynamic response of plant growth as affected by the dynamic change of nutrient solution temperature in hydroponic cultivation.

2. MATERIALS AND METHODS

2.1 Plant materials

In this study, Chili pepper (*Capsicum annum* L. cv. Takanotsume Togarashi, Takii seed, Japan) was used to identify the response of plant growth to the change of nutrient solution temperature. Then, the seedlings were transplanted into the measurement system after 35 days from sowing. The experiments were carried out in a growth chamber (2.5×2.5×2.0m; NK System, Nippon Medical & Chemical Instruments Co., Ltd., Japan) where the environmental factors were controlled. Table 1 shows the environmental factors settings used during the experiment.

A deep flow technique (DFT) hydroponic system was used to grow plants inside a growth chamber where the nutrient solution (EC) controlled at 2.3 ± 0.2 dS m^{-1} (Otsuka Vegetable Life A, OAT Agrio., Ltd, Japan). Five random patterns of nutrient solution temperature in the range of 15-37ºC were applied during the measurement in order to acquire sufficient information about the dynamic response of the physiological plant to the nutrient solution temperature. For realizing the nutrient solution temperature control, each pattern which consists of three plants was equipped with a NETC-3 thermostat (Newmarins Co. Ltd., Japan) to control nutrient solution temperature using a ceramic water heater and cooling water circulator.

2.2 The responses of plant growth measurement

The responses of plant growth as affected by the change of nutrient solution temperature were estimated through the change of the fresh weight of the plant. The fresh weight of the plant provides direct information on the status of the plant, and also an indicator for monitoring plant growth (Oda and Tsuji, 1992; Chen et al., 2013; Helmer, Ehret et al., 2005). In this study, a unique measurement system consisted of a load cell CZL635 micro load cell (Phidgets Inc., Canada), load cell support structure, and plant holder was developed (Figure 1). Load cell based plant weight measurement has been used in the various plant development monitoring system, i.e., (Helmer et al., 2005) developed Crop*Assist* to measure growth and water use for a tomato plant. However, due to the plant root was soaked in the nutrient solution; consequently, the weight of plant root was ruled out by the buoyant force. Therefore, the plant weight measured by measurement was only the plant shoot. A five-minute interval data sampling was applied to measure the change of plant weight during the experiment. Data were acquired and stored on a local computer and then relayed to the cloud data storage as a backup system.

2.3 Identification using LSTM networks

ANNs were developed for identifying the dynamic response of plant growth as affected by nutrient solution temperature through black-box model simulation. The black-box simulation means that the ANNs approach to time series prediction is not necessary to know the information regarding the process. By mimicking the biological human learning process, ANNs identifying the nonlinear relationship between the input and output signal of a system with their high learning abilities (Hinton, 1992). There are various

ANNs' architectures that have been developed in order to solve particular problems. One of the ANNs' architectures that has been demonstrated its good performance results for the development of a time series nonlinear system model is long short-term memory (LSTM) networks (Hochreiter and Schmidhuber, 1997; J. Chen et al., 2018). LSTM networks are the development of recurrent neural networks with an additional LSTM layer in the architecture. Each cell in the LSTM layer consists of information structures (gate) that regulate the information throughout the cell (Hochreiter and Schmidhuber, 1997). Figure 2 shows the gate structure in each LSTM cell; it consists of a forget gate layer, an update gate layer, and an output gate layer (Gers et al., 2015). The LSTM layer is essential in dealing with long-term dependency in a dynamic system, something that in a standard recurrent neural networks are lacked. Meanwhile, for a better generalization and to prevent the model output from overfitting, a dropout layer was added to the networks. The architecture of the LSTM networks used in this study is shown in Figure 3.

Tabel 1. Environmental factors settings inside the growth chamber during the experiment

Environmental factors	Unit	Environmental set points	
		Day	Night
Photoperiod	h	12	12
Photosynthetic active radiation	µmol m^{-2} s^{-1} PPFD	270	0
Air temperature	°C	25±1	20±1
Humidity	% RH	55±5	70±5

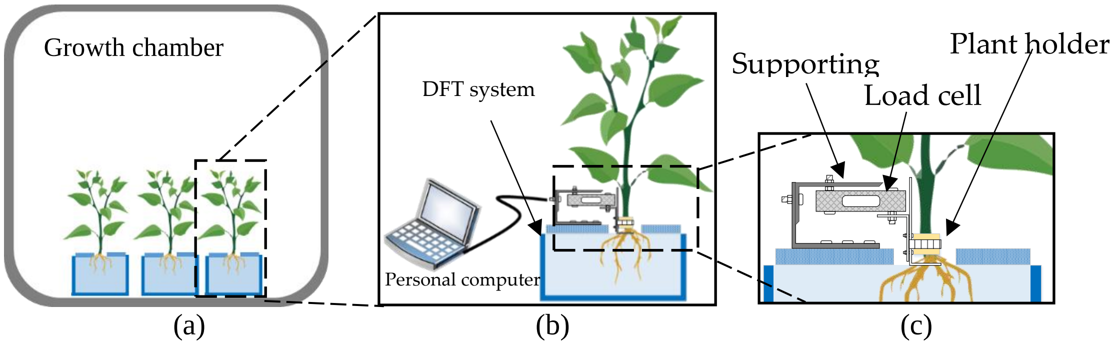

Figure 1. (a) Design of experiment inside the growth chamber; (b) plant growth measuring system using a load cell sensor; and (c) load cell support structure, and plant holde

2.4 Hyperparameter optimization

The performance of the ANNs algorithm depends on their hyperparameter settings. The optimal hyperparameter settings lead to better performance of the ANNs model. For LSTM networks, the prediction accuracy depends on hyperparameter, i.e., learning rates, regularization, the number unit per layer, and dropout rates (Hochreiter and Schmidhuber, 1997). Searching the optimal hyperparameter settings through a manual method could be stressful and time-consuming. Therefore, an optimization algorithm was used to search the optimal hyperparameter settings. In this study, Bayesian Optimization was applied to search the optimal hyperparameter settings. Bayesian Optimization has been known as a useful tool for hyperparameter optimization of various machine learning algorithm (Wu et al., 2019). In order to apply the algorithms, the MATLAB® Deep Learning Toolbox™ version R2019a (MathWorks® Inc., Natick, Massachusetts, USA) was used to create and simulate LSTM models.

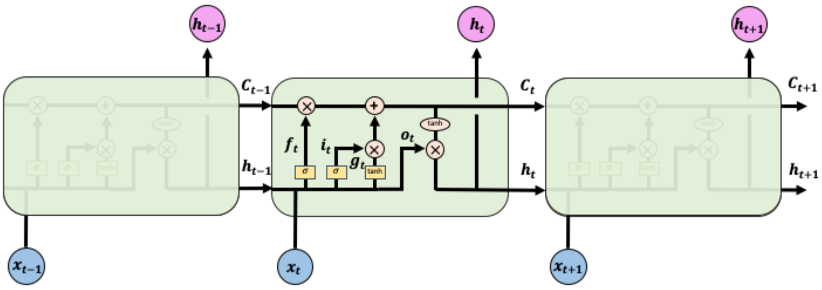

Figure 2. The repeating module in an LSTM cell structure which consists of a forget gate layer, an update gate layer, and an output gate layer to regulate the information through the layer. By using this gate structure, the LSTM networks can avoid the long-term dependency problem.

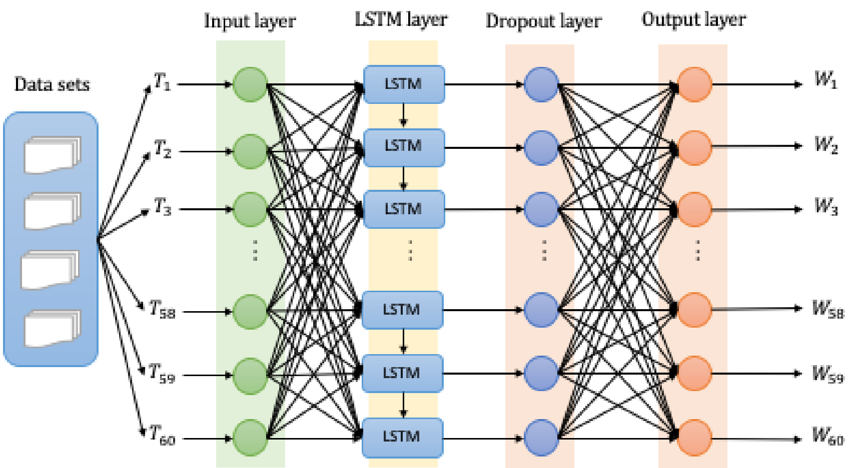

Figure 3. The LSTM networks architecture to identify the response of plant growth to nutrient solution temperature.

2.5 Data splitting

In machine learning, to generate a robust and unbiased model, the datasets were divided into three categories (Kuhn and Johnson, 2013), i.e., training, validation, and test sets. The training and validation datasets were used during the training process of the ANNs model. Training datasets are essential for the learning algorithm to fit the model. Meanwhile, validation datasets are useful for generalization during the training, which prevents overfitting through early stopping procedures. Meanwhile, the last data set were used to evaluating the model through cross-validation.

2.6 Measuring model performance

In order to measure the accuracy and eval uate the performance of the trained model, root mean squared error (RMSE) was used. The R MSE calculates the error variance of predicted and observed values, where the lower the value or the closer to zero is the better model perfor mance for RMSE, which are given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (1)$$

where n is the number of data points, y_i is the actual value or network output, and $\hat{y}_i$ is the predicted value.

3. RESULTS AND DISCUSSION

3.1 The responses of plant growth as affected by nutrient solution temperature

The development of an automated plant weight measurement system based on a micro load cell allows us to measure and monitor the development of plant growth during cultivation in a continuous and non-destructive manner. In Figure 4, five types of responses of plant growth as affected by the change of nutrient solution temperature obtained during 60 days of measurement in hydroponic. The measurement period corresponds to the early growth stage or vegetative stage of the plant. The responses of plant growth were represented by the growth rate in plant weight. This variable shows the changes in plant weight over time, which is a sensitive measurement to the response of plant growth. Therefore, this variable was used as the output variable for identification using LSTM networks. Meanwhile, the input variable is the nutrient solution temperature.

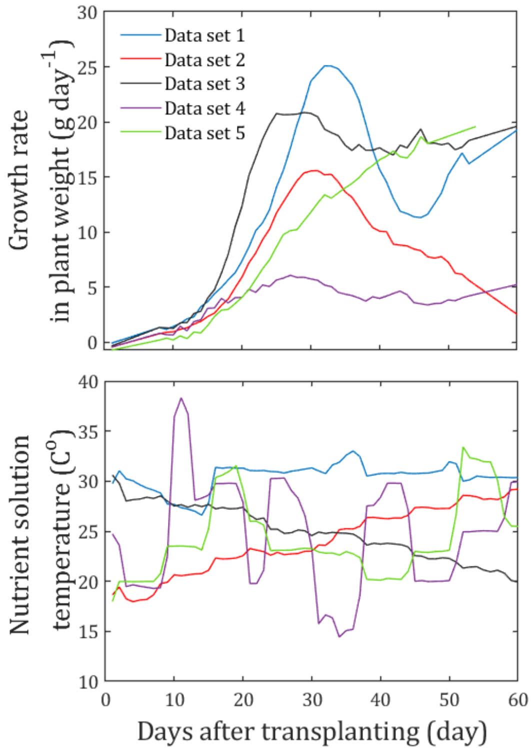

Figure 4. Dynamic response of plant growth as the change of nutrient solution temperature used for model identification

3.1 Development of LSTM networks model results

To train the LSTM networks optimally, the network architecture, as shown in Figure 3, must be specified by determining the hyperparameter settings. Figure 5 shows the hyperparameter tuning process using the Bayesian optimization algorithm. The objective function was defined by minimizing the regression error on the validation datasets as represented by the RMSE values. During Optimization, the hyperparameter values were tuned based on an optimization algorithm to find the minimum objective value function. The result shows that based on the evaluation from 80 LSTM networks models, the best model was reached at 0.799 of RMSE value. Therefore, the hyperparameter settings from the best model were selected for identification.

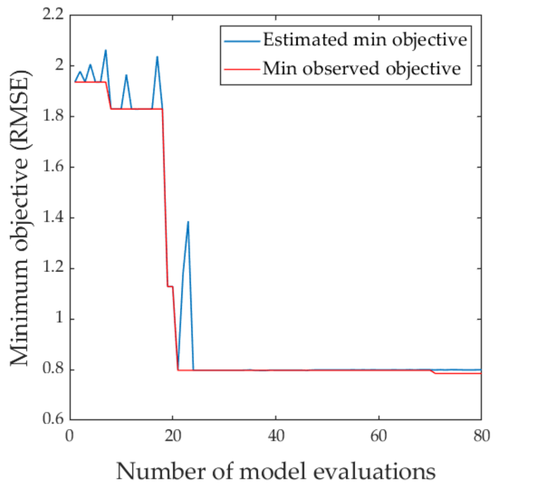

Figure 5. Objective value (RMSE) generated during the optimization process using the Bayesian optimization algorithm. An optimization algorithm was used to search the optimal hyperparameter settings by evaluating its model performance

Figure 6 shows the comparison of the estimated and observed value of growth rate in plant weight as affected by the change of nutrient solution temperature. The estimated value was obtained from the simulation of the identified model in Figure 5. It shows that the estimated response correlated closely with the observed response with the RMSE value is 0.735 gr. This result suggests that the LSTM networks algorithm could be useful to predict the response of plant growth as affected by nutrient solution temperature in a promising accuracy.

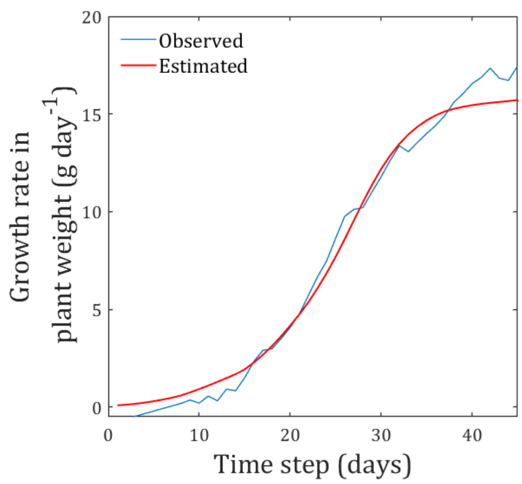

Figure 6. Comparison of estimated value, generated from simulation using identified LSTM networks and observed value from independent test dataset for cross-validation

4. CONCLUSIONS

In this paper, the development of a dynamic model using long short-term memory (LSTM) networks was presented to identify the response of plant growth to nutrient solution temperature. The LSTM networks showed a promising result in modeling the system. It suggests that the identified model in this study could be useful to model the response of plant growth as affected by the change of nutrient solution temperature.

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