GREENHOUSE MODELING AND SIMULATION FRAMEWORK FOR EXTRACTING OPTIMAL CONTROL PARAMETERS

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ABSTRACT

In a greenhouse system, a control is important to allow optimal growth conditions for crops. However, because testing the greenhouse for real conditions requires much time and money, the modeling-and-simulation approach is necessary to predict and improve the greenhouse environment. There is much research related to greenhouse control, there is a lack of research on applicable frameworks for real greenhouses. Therefore, this paper proposes a greenhouse modeling-and-simulation framework to extract optimal control parameters. The proposed work is composed of three parts: system identification, controller design, and optimization. The plant model is built through system identification, and the model is controlled by the controller, which is affected by disturbances. This simulation is repeated through design of experiments to optimize the control parameters. This paper presents an experiment with real greenhouse data from Jinju, Korea to show the usefulness of the proposed framework. It gives insight into the decision of choosing control parameters and helps to raise agricultural productivity.

INTRODUCTION

Greenhouse control to create a favorable environment to improve crop development is an important problem. Proper control can help maximize the productivity of crops. Thus, maintenance of environmental parameters, like greenhouse indoor temperature, humidity, CO_2 levels, and so on, according to the plant growth cycle, is required. There are many elements used to control these parameters in the greenhouse control system, for example ventilators (or windows), heaters, or shading screens. However, it is difficult to find optimal control parameters according to the specifications of greenhouses because constructing real greenhouses requires much time and can be expensive.

Modeling and simulation (M&S) can be the best method to overcome this problem. We can easily extract the optimal parameter set for a greenhouse through the M&S framework. Then, we can obtain the optimal growth conditions for crops by applying the parameter set into the real control system (Figure 1). Because the greenhouse control system is too complex to model completely, it is necessary to analyze and classify the system according to the objective of M&S. The greenhouse system is largely composed of plant, sensor, controller, actuator, and environment. As depicted in Figure 1, they work as follows. The operation result occurs through the controller and actuator when control parameters are set up in the controller. Then, the plant model generates outputs (indoor temperature and humidity). The outputs reach the controller as a feedback. Such a process is executed in every clock recursively, and consequently, the plant outputs can be adjusted close to the set point that we want to acquire.

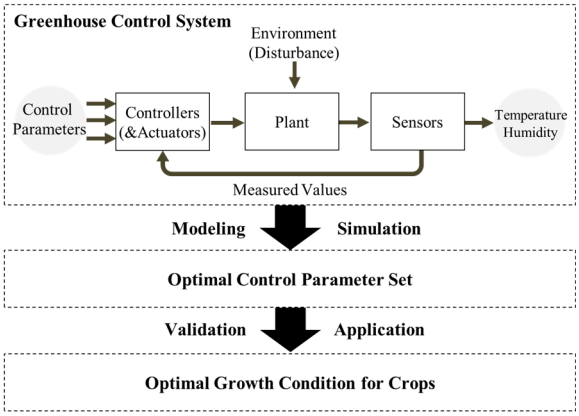

Figure 1: Overview of Greenhouse Control System

There is a glut of research related to the modeling of greenhouse control systems. The details will be described in the next section. However, there is a lack of research providing an overall framework that is possible to apply directly to a real greenhouse. Therefore, this paper proposes a greenhouse M&S framework to extract optimal control parameters. The control parameters are important elements that decide the specification and performance of the controller. The proposed framework includes the entire process, including system identification, along with control and parameter optimization.

This paper is organized as follows. Previous works related to our study are briefly introduced. Then, our proposed framework for extracting optimal control parameters using a neural network is described. Finally, an experiment with real greenhouse data is provided.

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RELATED WORK

There has been much research regarding modeling greenhouse control systems. Some research has focused on how to model and predict the greenhouse model (Cunha 2003). This research applied several methods, like physical modeling (Bot 1991), autoregressive exogenous (ARX) modeling, and artificial neural network (ANN), to create plant models. They showed pros and cons of each modeling approach, but they did not consider the part of the controller model and the parameter optimization of the greenhouse environment.

In control fields, there has been research that applied several techniques to control the greenhouse climate (Hagan and Demuth 1999). A proportional-integral-derivative (PID) controller is one of the representative methods to control the feedback system, and it is frequently adapted to the greenhouse model (Cunha et al. 1997). Other researchers have applied robust adaptive control to implement the controller (Bennis et al. 2008; Luan et al. 2011). Robust control is an approach that refers to the control of uncertain plants with unknown dynamics subject to uncertain disturbances (Chandraseken 1996). They build the plant model through physical modeling, then implement a controller through the theory of robust control.

These researches provides controllers with high performance. However, they do not consider the disturbances that vary with time. Also, they are hard to be implemented and applied to the real greenhouse control system directly. There is no research on how to provide a practical framework that is applicable to a real greenhouse system. For this, the framework should include all of plant modeling, controller modeling, and parameter optimization.

Therefore, we propose an M&S framework for extracting greenhouse control parameters that is applicable to the real greenhouse system in this paper. The next section will describe this proposed framework in detail.

GREENHOUSE M&S FRAMEWORK

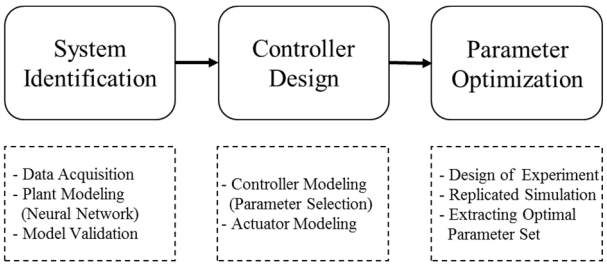

Figure 2: Overall Process of Proposed Framework

In this section, we propose a greenhouse M&S framework for extracting optimal control parameters. This proposed framework helps to draw optimal parameters by acquiring greenhouse data, regardless of the specification of the greenhouse. As shown in Figure 2, it is mainly composed of three parts: system identification, controller design, and parameter optimization. In the system identification step, we built a plant model with acquired greenhouse data using ANN. In the control step, the temperature and humidity were controlled by the control algorithm. Finally, in the parameter optimization step, we drew the optimal control parameter set through repeated simulations designed by design of experiments (DOE).

In this paper, our target system is a greenhouse located in Jinju, Korea. Its specification is concretely depicted in Table 1. Our proposed framework is applicable to this greenhouse as mentioned below.

Table 1: Specification of Greenhouse

Type	Specification
Location	Jinju, South Korea
Dimensions	30 x 90 x 7.5 (m)
Date / sampling time	2015, April~June / 1 minute
Kind of crop	Tomato
Sensors	Temperature, humidity, CO_2, wind speed, light density, etc.
Actuators	Window, heater, screen, etc.

Part 1: System Identification

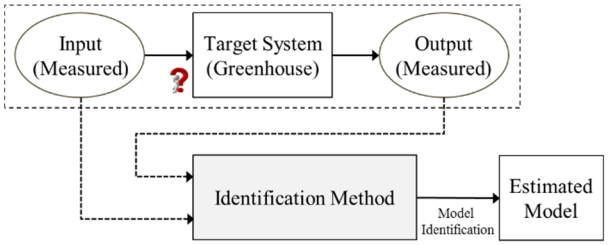

Figure 3: Basic Concept of System Identification

System identification is a process used to build a mathematical model of the dynamics of a system from measured data (Nelles 2000). Figure 3 shows the concept of system identification. The design of the control system requires a system-identification process to build a model of the dynamics.

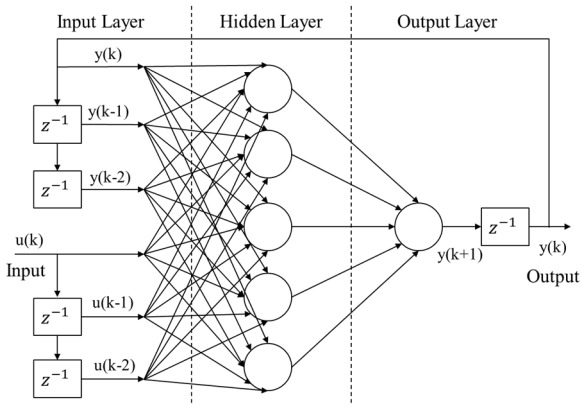

Figure 4: Tapped-Delay-Line Neural Network

There are several methods of system identification (Ljung 1987), like ANN. We used ANN to identify the plant model of the greenhouse in the proposed work (Narendra and Parthasarathy 1990). ANN is a machine learning approach that is inspired by biological neural networks and composed of a large number of highly interconnected neurons. During the learning, the strengths of neuron connection (weights) are changed in order to calibrate the model. ANN can predict the future behavior of the system precisely (Sjöberg et al. 1994). As shown in Figure 4, we use tapped-delay-line neural network (TDLNN) for the prediction of time series (Gupta et al. 2004).

In our system identification, we first acquired and analyzed the observational greenhouse data to use them as training data. They were classified into inputs, outputs, and disturbances. It was important to include parameters mainly affecting the plant model and exclude the other minor ones before we identified the plant model. In this paper, we use greenhouse parameters as depicted in Table 2 to identify the model through TDLNN. Control inputs and disturbances were used for the inputs of neural network, and control outputs were used for the outputs of neural networks.

Table 2: Parameters Used in Plant Model

Type	Parameter	Description
Control Inputs	Pw (%)	Window Angle
	Ht (%)	Heater
Control Outputs	Ti (℃)	Indoor Temperature
	Hi (℃)	Indoor Humidity
Disturbances	To (℃)	Outdoor Temperature
	Ql (W/m^2)	Light Quantity
	Sw (m/s)	Wind Speed

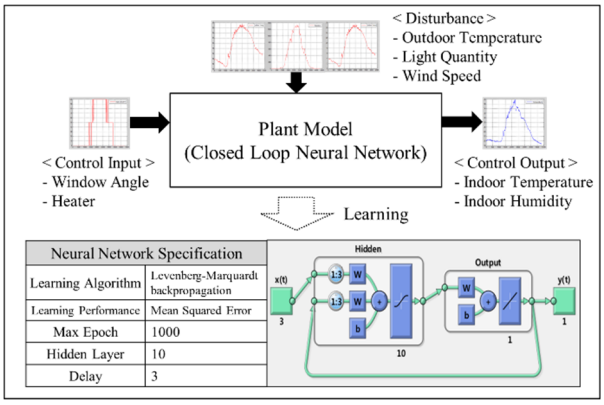

Figure 5: System Identification Process

In this paper, we use the Lavenberg-Marquardt optimization technique as a learning algorithm (Marquardt 1963), and mean squared error for a measurement of learning performance. Figure 5 shows the identification of the plant model and its specification. Also, Figure 6 represents the comparison result between real indoor temperature and predicted indoor temperature using the identified plant model. It shows that the identified plant model reflects well the real greenhouse plant.

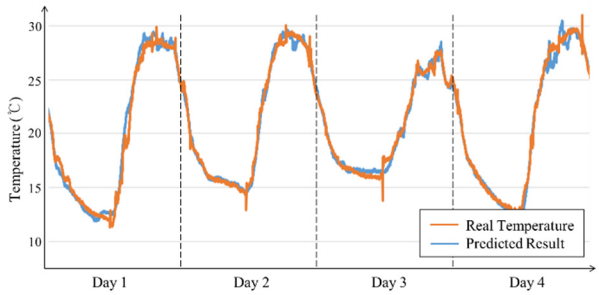

Figure 6: Result of System Identification

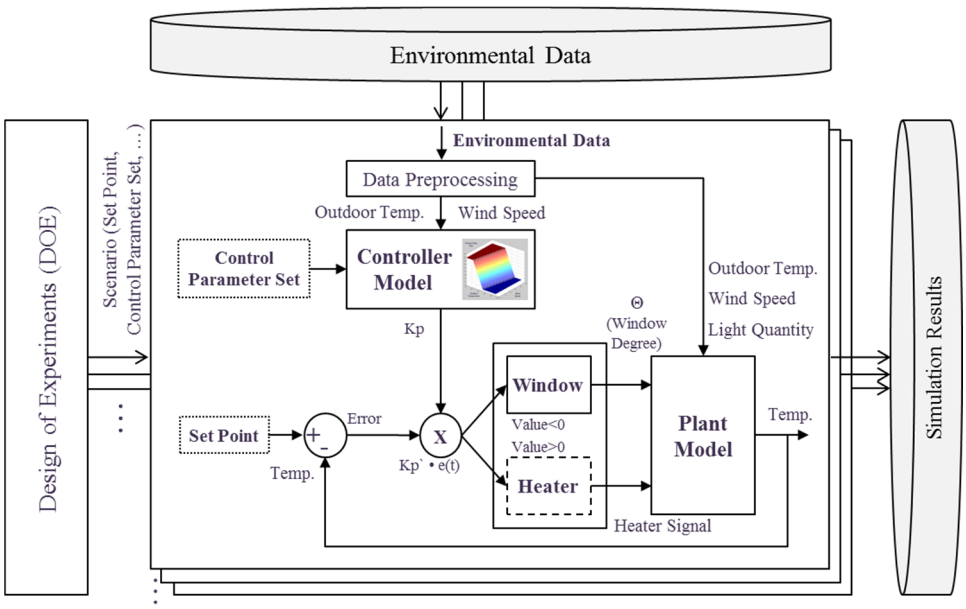

Figure 7: Overall M&S Framework

Part 2: Controller Design

After the process of system identification, we used the plant model to control the greenhouse system. Even though there were many elements to be controlled, we focused on the window and heater. They played an important role in decreasing and increasing inner temperature and humidity. In this paper, we only considered the window control in order to focus on one result. A P controller is generally used to control the window in the greenhouse. The proposed framework applied the concept of a P-band for the P control (Kamp 1996). A P-band determines the opening angle of the window according to the difference between the measured point and the set point. It is the reciprocal of the proportional gain constant (K_P) generally used in the P controller.

Table 3: Description of Control Parameter Set

Parameter	Description
max.out.temp	Maximum threshold of outdoor temp.
min.out.temp	Minimum threshold of outdoor temp.
max.wind.spd	Maximum threshold of wind speed
min.wind.spd	Minimum threshold of wind speed
max.pband	Maximum threshold of P-band
min.pband	Minimum threshold of P-band
deg.win.open	Window opening angle with one execution

In this paper, we used a modified P controller that had a variable P-band (= 100 / K_P) value, not a fixed P-band. The controller reflected outdoor temperature and wind speed from the greenhouse data dynamically because the P-band value is influenced by the parameters. (Kamp 1996) For example, the P-band value decreases when the temperature rises, and conversely, it increases when the wind speed increases. The variable P-band graph determined by outdoor temperature and wind speed is shown in Figure 8. However, it is hard to know the optimal shape of the graph (including gradient, maximum, and minimum threshold value) that can maximize the growth of the crops. So, the optimization step is required to find the optimal control parameters that determine the shape of the graph.

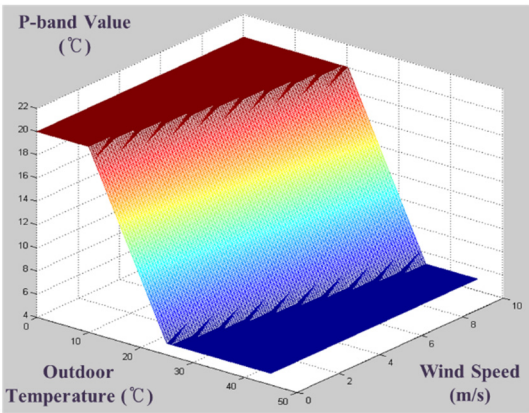

Figure 8: Decision of P-band Value

Part 3: Parameter Optimization

After design and implementation of the controller, parameter optimization is required to draw an optimal control parameter set. The control parameters are the seven input parameters that determine the shape of the P-band graph (Figure 8), as shown in Table 3. They are actual parameters used in the greenhouse control system, using the controller as mentioned previously. When the shape of the graph changes due to these input parameters, indoor temperature and humidity are also affected. Therefore, replicated simulations should be performed in accordance with the designs that are made by DOE. There are various methods of DOE, like full-factorial design, central composite design, and Box-Behnken design, used to perform efficient experiments (Antony 2003). Using these DOE methods, we can find an optimal control parameter set (input), which has the lowest root mean squared error (RMSE) value (output). Figure 7 represents the overall M&S framework, including all of the parts.

EXPERIMENTS

In this section, we represent the experiments using the real greenhouse data to show the effect of the proposed work. We acquired the data from the greenhouse located in Jinju as mentioned earlier (Table 1).

Experimental Design

We designed experiments to acquire the optimal control parameter set, which would have the lowest RMSE value. To find the optimal control parameter set, we simply used full-factorial design. Table 4 shows seven parameters and their values in the greenhouse control system. A total of 15,625 simulation runs were required to find the optimal parameter set.

We used MATLAB/Simulink to implement our proposed work. We also used the six thousand sample data over four days to simulate the greenhouse control system, as depicted in Table 1.

Table 4: Parameter Set of Greenhouse Control System

Parameter (Input)	Value	Number
max.out.temp (℃)	23 ~ 27	5
min.out.temp (℃)	16 ~ 21	5
max.wind.spd (m/s)	1 ~ 5	5
min.wind.spd (m/s)	0	1
max.pband (℃)	18 ~ 22	5
min.pband (℃)	3 ~ 7	5
deg.win.open (%)	10, 15, 20, 25, 30	5
Total Executions	15,625 ($=5^6$)	

Experimental Results

We obtained an optimal control parameter set, which had the lowest RMSE value, through replicated simulations with DOE (Table 5). The RMSE of the simulation with the optimal set was 2.511, and the RMSE of real data was

4.195. That is, the adaptation of the optimal set led to a 40.1% performance improvement compared with real temperature, which did not need to be optimized. Figure 9 shows the graph of the control result using this parameter set. In this experiment, the performance improvement is only showed in the part of cooling, which is controlled by the window, because we did not use the control data of the heater.

Table 5: Simulation Result: Optimal Parameter Set

Parameter	Optimal Value
max.out.temp (℃)	25
min.out.temp (℃)	19
max.wind.spd (m/s)	1
min.wind.spd (m/s)	0
max.pband (℃)	19
min.pband (℃)	4
deg.win.open (%)	10
RMSE improvement	40.1%

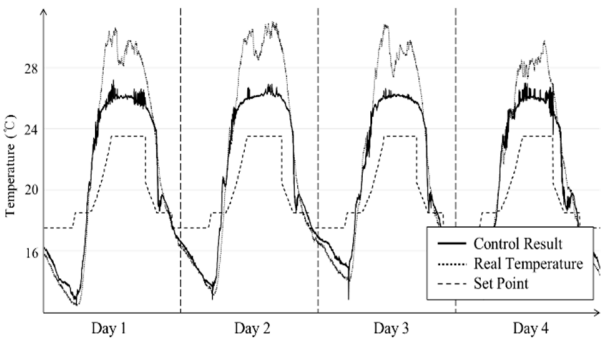

Figure 9: Simulation Result: Predicted Temperature

The result shows that the indoor temperature was controlled nearer to the set point through the adaptation of the optimal parameter set. That is, periodic simulation and adaptation of the parameter set can help to maintain more suitable indoor temperatures for the crops without any trial and error. The user only needs to input the parameter set into the greenhouse control system. Consequently, we know that the proposed M&S framework can provide optimal growth conditions by predicting the greenhouse environment.

CONCLUSIONS

This paper proposed a greenhouse M&S framework to draw optimal control parameter set. It is hard to test the real greenhouse due to the time needed and cost; thus, the M&S approach was applied to predict and improve the greenhouse environment. The proposed work was composed of three parts: system identification, controller design, and optimization. The plant model was built through system identification, and the model was controlled by the controller, which was affected by certain disturbances. This control simulation was repeated with DOE to optimize the control parameters.

In this paper, we used the data acquired from the greenhouse in Jinju, Korea to show the usefulness of the proposed framework. We drew the optimal control parameter set by applying the data taken over four days to the framework, which allowed us to verify that it had an improved control performance. This result means that the framework can give insight into the decision of control parameters and raise agricultural productivity.
For further work, we will fully automate the each step of the framework to adapt it to the real greenhouse system. Also, we will apply various techniques about neural network, control, and optimization for the performance improvement.

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