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学位論文全文に代わる要約
Extended Summary in Lieu of Dissertation

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Name

学位論文題目：
Title of Dissertation

Environmental Condition Assessment of Tomato Production Systems based on Speaking Plant Approach for Supporting Intelligent Control Systems

(知的制御システムを支援するためのスピーキング･プラントアプローチに基づくトマト生産システムの環境条件評価)

学位論文要約：
Dissertation Summary

Environmental control of plant production systems affects crop productivity and quality. The efficiency of plant production in plant factories or greenhouses significantly depends on adjusting several components, particularly the internal temperature, relative humidity, carbon dioxide (CO_2) concentration, and water management. Optimization of these components can lead to better cultivation systems.

A concept that controls and manages the optimal environment for cultivation on the basis of the diagnosis of the growth status of a plant is known as the “speaking plant approach”. The concept of Speaking Plant Approach (*SPA*) was proposed and *SPA* based intelligent control technique consisting of a decision system and feedback control system was applied to the optimizations of tomato cultivation.

Early stage of fruit diagnostic systems using Artificial Neural Networks

The decision system consists of artificial neural networks (*ANN*), which is used for supporting the development of machine vision through the flower recognition. From the study, it is known that the shape of tomato fruits was affected by the flower shape. Fruit shape is one of the important quality parameters in market, and the uniform fruit-shaped is becoming our goal in the cultivation. In this study, the flower shape analysis was used as the computer vision technique for developing flower recognition program.

One of the objectives of greenhouse cultivation is to achieve a year-round production of high quality produce that meet the customer satisfactions. Flavor, color, shape and texture are all important characteristics of fresh tomatoes. Fruits should be of uniform shape, symmetry and size. The shape of tomatoes can be recognized from its floral/flower morphology. Here later, study of the morphological tomato flower and its influence on shape will be discussed furthermore.

During the cultivation it was found that, some tomato fruits had grown into unusual shape. From the investigation it was known that the unusual shaped fruits came from the malformed flowers. Generally, tomato flowers is characterized with bright yellow color, 6–7 combination of petals, and circle-shaped of anther cone (Fig. 1A). Meanwhile, malformed flowers as shown in Fig. 1B has uncertain number of petals and irregular-shaped of anther cone.

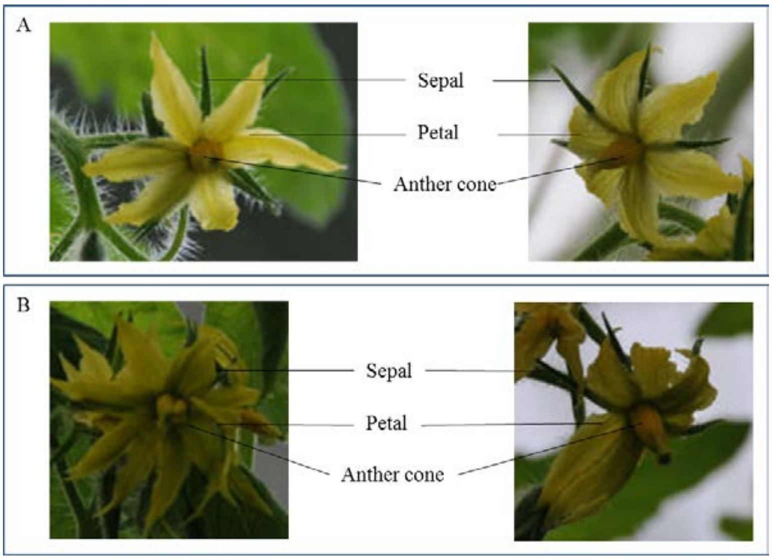

Fig. 1 Structure of the tomato flower

Malformations were associated with the low temperature exposure during early flower development (Barten et al., 1992) and stress conditions such as water stress (Hatou et al., 2011). Water stress caused a big influence in the growth point of the plants where flower is formed. As a result some symptoms appear, such as: the increase of the number of petal and flower size, also an oval-shaped of the anther cone. As a consequence, abnormal fruits of low economic value are produce from these flowers (Fig. 2).

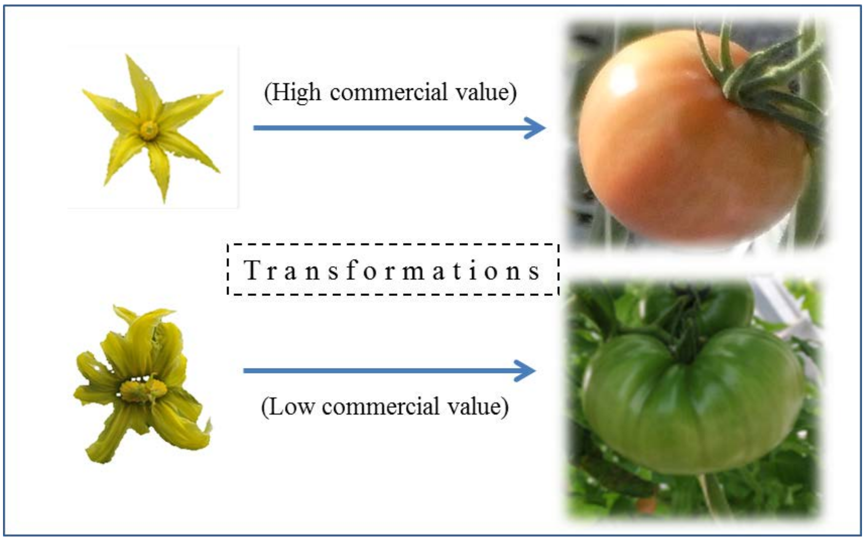

Fig. 2 Fruits transformation from its flower

Currently, removing of the malformed flowers to decrease unwanted-shape of fresh fruits still relies on the operator (growers). The assessment of the flower shape, depend on the human operator expertise. In the future, where the automation works take control, the development of machine vision becoming important in order to assist in autonomous decision making. The study of the flower recognition in supporting fruit diagnostic systems on early stage was developed using the artificial neural networks (*ANN*).

Input preparations

In this study, tomato flowers were classified into two groups: normal and abnormal flower, as shown on Fig. 3. Normal flowers were characterized with the uniform-shaped of petals and a circle-shaped of anthers, while the abnormal flowers have higher number of petals than normal, and an oval-shaped of anthers.

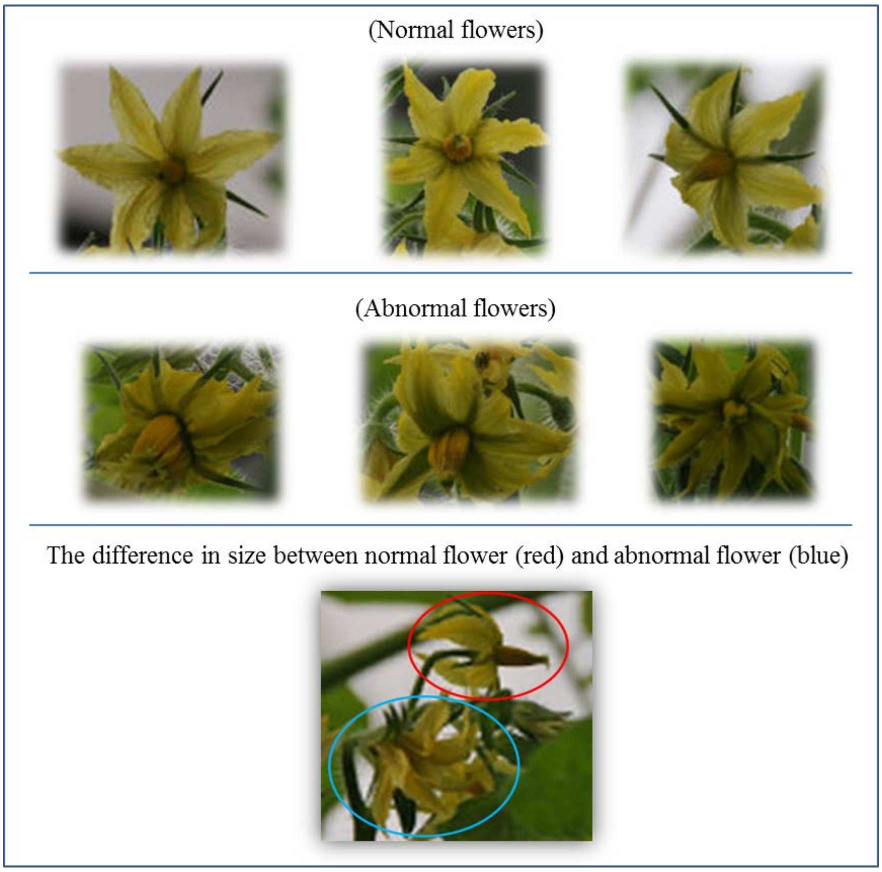

Fig. 3 The appearance of normal and abnormal flowers

Proposed Methodology

A typical pattern recognition system is shown in Fig. 4 and the major steps are explained in consecutive sub-sections.

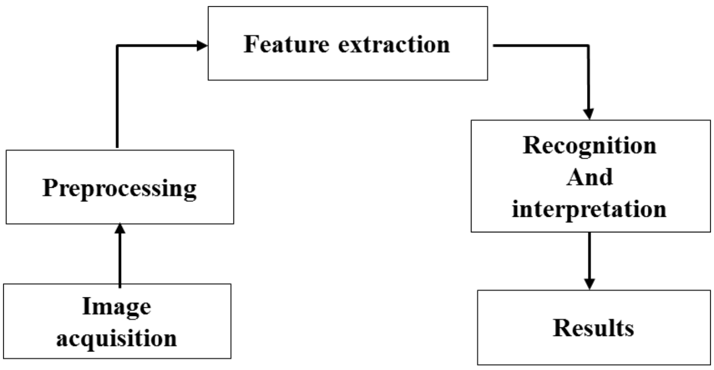

Fig. 4 Flowchart of proposed scheme

– Image acquisition

Al flower images were acquired using a digital camera from the front side.

– Pre-processing

Image pre-processing does not increase the image information content, and it is important to suppress information that is not relevant to the analysis task (i.e. background subtraction). The image must first be processed using the same technique to standardize the results. In order to extract any specific information, image pre-processing steps are carried out before the actual analysis of the image data. Pre-processing refers to the initial processing of input image to eliminate the noise and fix the distorted data. Fig. 5 illustrates the pre-processing techniques used in this study.

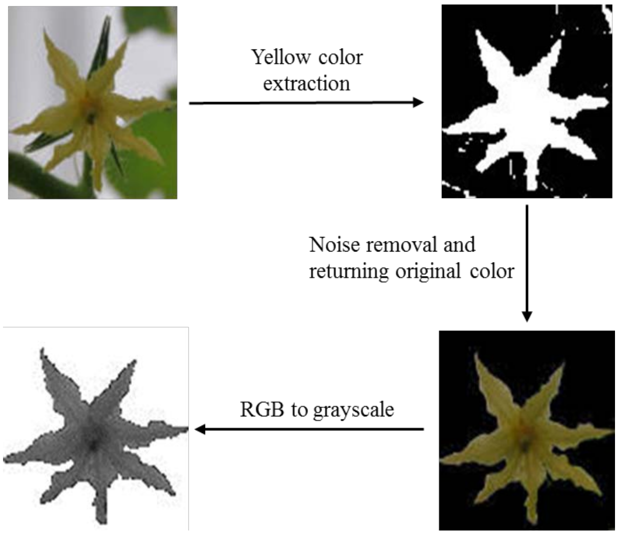

Fig. 5 Pre-processing steps performed on a flower image

– Feature extraction

Image features are meaningful and detectable parts of an image. Features are associated to interesting scene elements in the image formation process. In this study the shape feature was selected due to its specific pattern on both images, normal and abnormal flower. Two kinds of images were obtained from this process: whole-part image and the image of anther cones, which later called reproductive-part image of a flower. Later, the performance of neural networks program will be tested using these two kinds of images.

– Recognition and interpretation

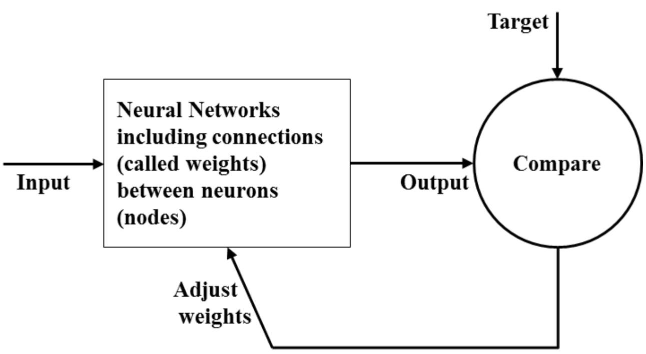

Fig. 6 Scheme of learning phase in pattern recognition using Neural Networks

A neural network, illustrated in Fig. 6, consist of neurons (nodes), arranged in layers, which convert an input vector into output.

Implementation of Artificial Neural Networks (ANN) for Flower Recognition

The program was written in C# (C-Sharp) computational programming language using the Microsoft Visual Studio program (Microsoft Inc.). Three-layered neural networks were constructed, which consist of input layer, a hidden layer, and output layer. The input was feed into the trainer classifier, which will be classified with the images on data sets. As results, a close-matching pattern from data set for the given input was used to assess the performance of the program. The combinations of neuron numbers in the hidden layer was examined to get the best performance in term of accuracy rate of the pattern recognition.

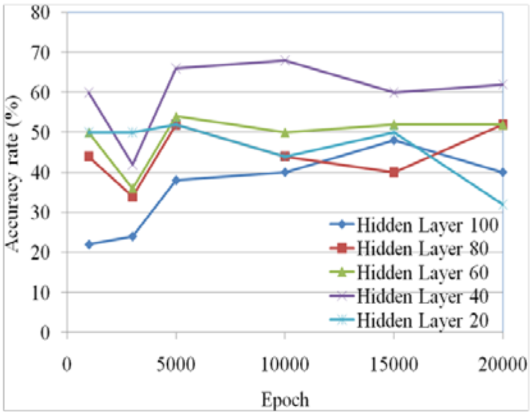

Fig. 7 Relationships between epoch and the estimated accuracy (%) of whole flowers

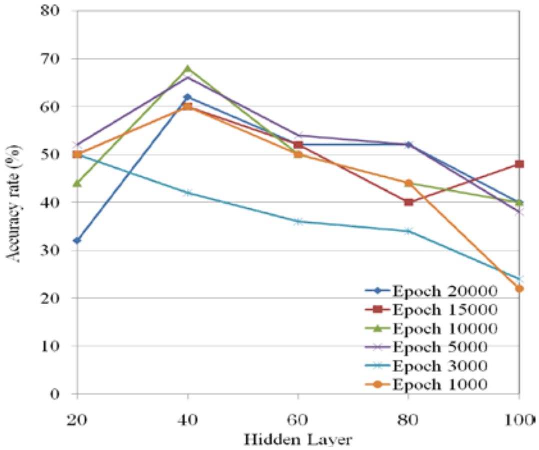

Fig. 8 Relationships between the neuron number in the hidden layer and the estimated accuracy (%) of whole flowers

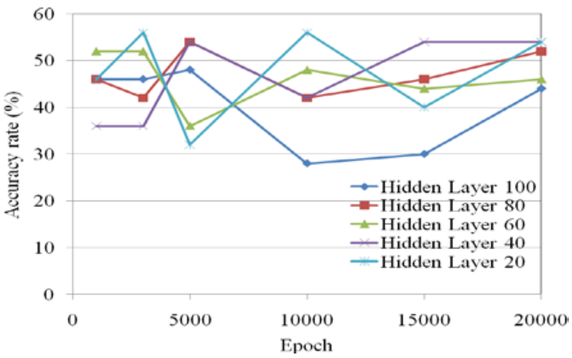

Fig. 9 Relationships between epoch number and the estimated accuracy (%) of reproductive part

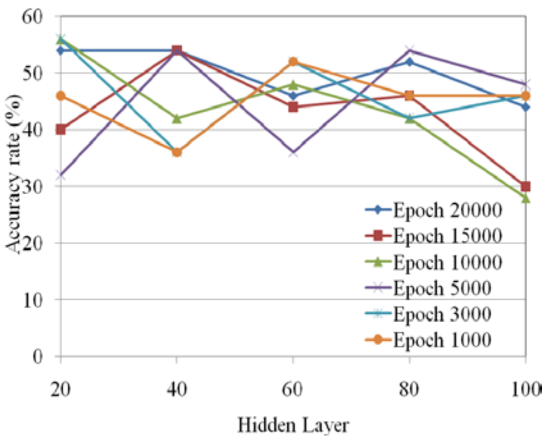

Fig. 10 Relationships between the neuron numbers in the hidden layer and the estimated accuracy(%) of reproductive part of flower

Combinations of neuron numbers in hidden layer and maximum epoch were performed and applied to the constructed neural networks program in order to achieve best accuracy rate. The best performance of 40 neurons in hidden layer (Fig. 8) with the maximum epoch of 10000 (Fig. 7), was produced the highest accuracy rate in recognizing the pattern of flower. The result has not improved although numbers of hidden layer is increased more than this. Meanwhile, the best performance of recognition using reproductive image of tomato flower was obtained with the combinations of 20 neurons in hidden layer (Fig. 10) and maximum epoch of 3000 (Fig. 9). The accuracy rate of image recognition by using whole part of flower image was resulted the better performance in term of accuracy rate. For the further development of machine vision, these images can be the alternatives of input materials for the image recognition program.

Yield prediction using Artificial Neural Networks

We also have studied the implementation of computational intelligent techniques, in particular multilayer neural networks for modeling and predicting weekly fluctuations of harvest rate and fruit size of tomatoes. This estimation based on meteorological data and crop growth parameters collected during one full growing season in between 2011–2012.

The neural network model was constructed and implemented using the Neural Network ToolboxTM R2010a of Matlab® 7.10 (The MathWorks, Inc., Boston, MA, USA). One of the most common learning methods within neural networks, feed-forward back-propagation algorithm, was used in this study. Two types of data (climate data and growth parameters data), which calculated and measured during the cultivation periods were used as inputs, while harvest rate and fresh weight of tomatoes as outputs. The architecture of four layers of the feed-forward back-propagation network is represented in Fig. 11.

Artificial Neural Networks model

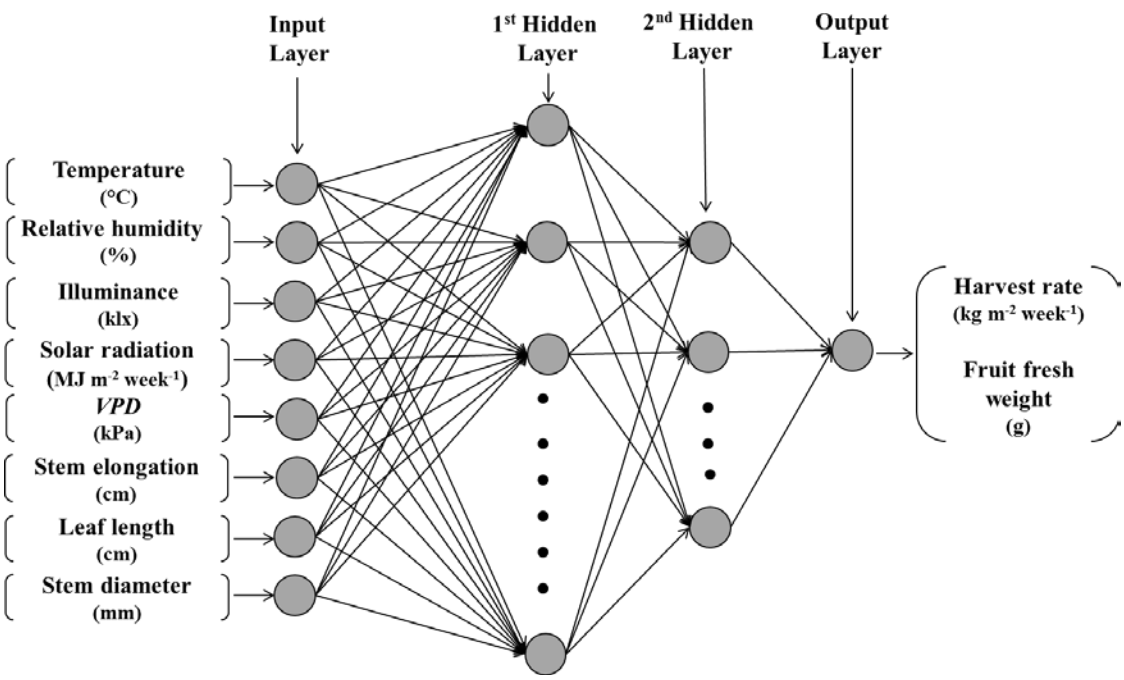

Fig. 11 The architecture of four layers neural networks model

The artificial neural networks (ANNs) were developed and tested for prediction of harvest rate and fresh weight of tomatoes based on eight input variables: air temperature, relative humidity, illuminance, solar radiation, vapor pressure deficit (*VPD*), stem elongations, leaf length, and stem diameter. The number of nodes in the input and output layers are restricted by the number of model inputs and outputs, respectively. There is no direct and precise way of determining the best number of nodes in the hidden layer. In this case, a trial-and-error procedure was used to determine the number of the hidden layer nodes. Among the various ANNs structures, the best model performance was produced by a four layers ANNs structure for both predictions. Combination of 8-15-5-1 for the total number of nodes (neurons) in input layer, 1st hidden layer, 2nd hidden layer, output layer, respectively, produce the smallest *MAE* (Fig. 12) for prediction of harvest rate of tomatoes. Meanwhile, for estimation of fresh weight of tomato fruit, the combination of 8-15-9-1 gave the best performance, as showed by the smallest *MAE* (Fig. 13).

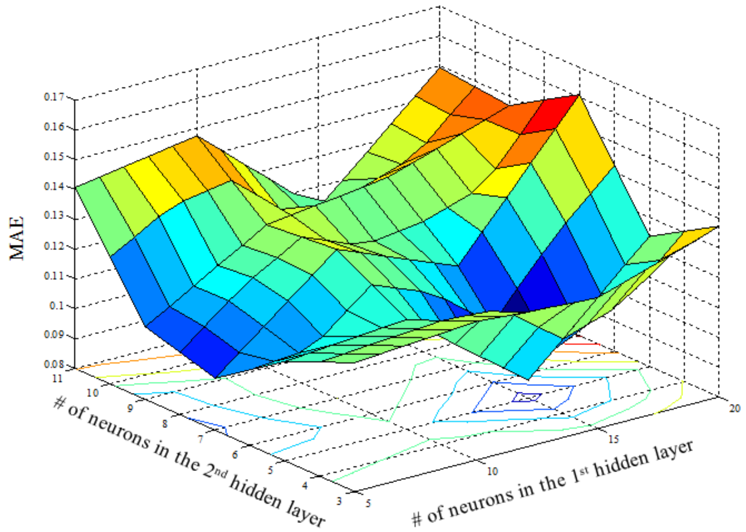

Fig. 12 Training *MAE* as affected by the number of neurons for the harvest rate estimation

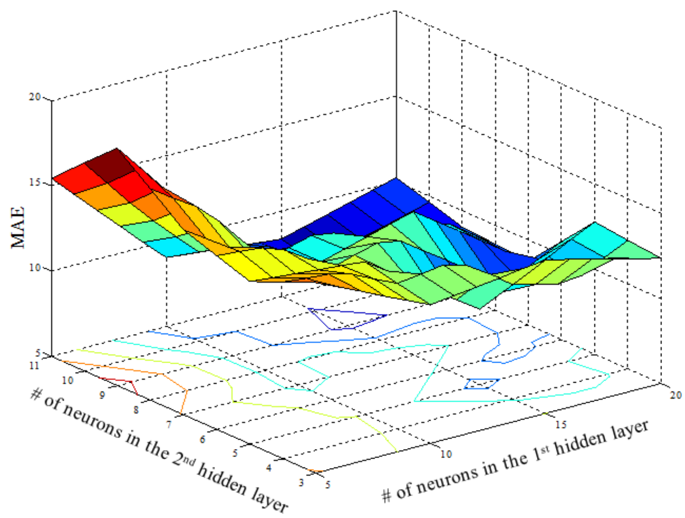

Fig. 13 Training *MAE* as affected by the number of neurons for the fruit fresh weight estimation.

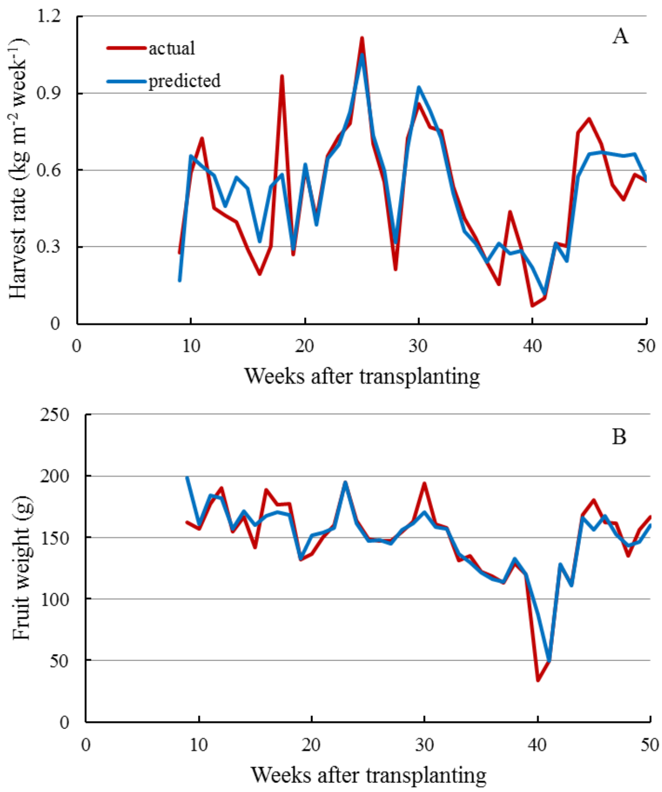

Fig. 14 Actual versus predicted of weekly harvest rate (A) and fresh weight (B) of tomatoes

A regression analysis between measured and predicted values by the neural networks model resulted in correlations coefficients (R^2) of 0.77 and 0.85 for estimation of harvest rate and fruit size, respectively. The artificial neural networks model is potentially an efficient and feasible tool for predicting harvest rate and fruit weight of tomatoes. The correlation coefficients between actual and predicted value on each of the parameter indicates the good performance of the neural networks.

Measuring and Estimating the Water Requirements of Plants

Another studies related to the required amount of water by crop was done due to its necessity in giving the proper irrigation and preventing the excess irrigation, by it means minimize chemical usage and improve on-farm water use efficiency. Crop water use is related to evapotranspiration (*ET*). Accurate determination of *ET* is essential to precisely compute crop water use and to assist growers for applying good irrigation management. An estimation based on a mathematical model to predict hourly evapotranspiration (*ET*) rates that occur inside a plant factory system was made using the Stanghellini model. The Stanghellini model is considered more appropriate for estimating the rate of *ET* inside the soilless culture of greenhouse tomatoes. The model requires some climatic data (e.g., solar radiation, air temperature, relative humidity, and wind speed) and plant growth parameters (leaf area index) as inputs.

Water balance and crop water use in the greenhouse

ET can be related to the water supplied by an irrigation system, the change in water stored in substrate media, and the volume of water drained out of the greenhouse. The water stored in the artificial substrate is constant; therefore, it was ignored when calculating *ET* in the present study owing to its limited influence. The *ET* rate of tomato (*Lycopersicon esculentum* Mill.) crop was measured using a weighing method.

ET mathematical model

The Stanghellini model includes calculations of *Rs* heat flux derived from the empirical characteristics of shortwave and longwave radiation absorption in a multilayer canopy (Stanghellini, 1987; Prenger et al., 2002). The crop growth parameter is also an important factor for determining crop water use. The Stanghellini model requires *LAI* for calculating the *ET* rate. *LAI* is used to account for energy exchange from multiple layers of greenhouse plants. During the observation period, *LAI* of the tomato crop grown inside the experimental site was 2.8–2.9 m^2 m^{-2}. The model proposed by Stanghellini (1987) is presented in equation as follows:

$$ET_o = 2.LAI.\frac{1}{\lambda}.\frac{\Delta.(R_n - G) + Kt.\frac{VPD.\rho.C_p}{r_a}}{\Delta + \gamma.\left(1 + \frac{r_c}{r_a}\right)}$$

where ET_o is the reference *ET* (mm d^{-1} and mm h^{-1} for a daily and hourly basis, respectively), *LAI* is the leaf area index in m^2 m^{-2}, Δ is the slope of saturation vapor pressure curve at an air temperature in kPa °C^{-1}, *Rn* is the net radiation in MJ m^{-2} d^{-1}, *G* is the soil heat flux in MJ m^{-2} d^{-1}, *VPD* is the vapor pressure deficit in kPa, ρ is atmospheric density in kg m^{-3}, C_p is the specific heat of air in kPa °C^{-1}, γ is the psychrometric constant in kPa °C^{-1}, *rc* and *ra* is the canopy and aerodynamic resistance, and *Kt* is a unit conversion (86400 s d^{-1} for ET_o in mm d^{-1}; 3600 s h^{-1} for ET_o in mm h^{-1}).

Results

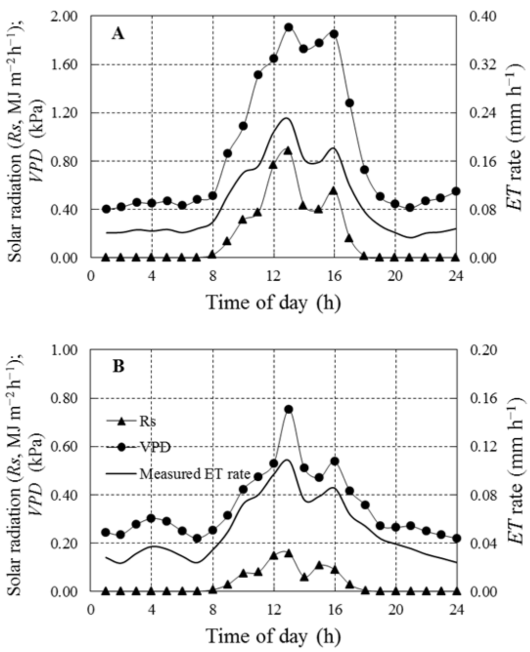

Fig. 15 The effect of solar radiation (*Rs*) and vapor pressure deficit (*VPD*) on the evapotranspiration (*ET*) rate of tomato crops as measured on a sunny day and a rainy day, respectively

Figure 15 shows the hourly (24-h) example of *Rs* and *VPD* measured from above the plant canopy and the *ET* rate for sunny and rainy days, respectively. *Rs* and *VPD* were very low in the morning. However, both the values increased when the sun rose; therefore, transpiration reached its maximum during midday. *Rs* values were the minimum at night and early morning. Water loss continued during this time, as observed in the graph. It was assumed that *ET* was driven by *VPD* at this specific time. *ET* tended to be more proportional to *Rs* on sunny days (Fig. 15A). However, *ET* tended to be more proportional to *VPD* on rainy days (Fig. 15B).

The relationships between *Rs* and measured *ET* and between *VPD* and measured *ET* are presented in Fig. 16A and 16B, respectively. The results showed a good linear relationship, according to the regression determination coefficient ($P < 0.05$ and 0.01).

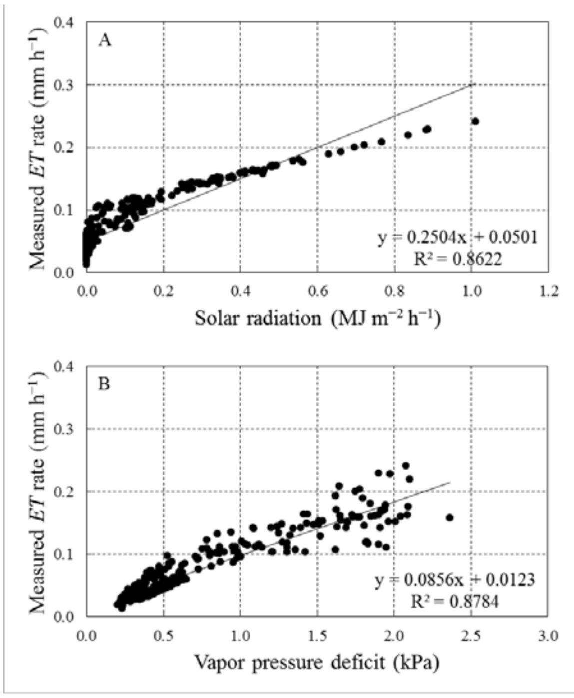

Fig. 16 Correlations between solar radiation (A), vapor pressure deficit (B), and measured evapotranspiration (*ET*) rate of tomato during the observation time

Hourly crop water use was measured with data from the irrigation event and from drainage and compared with data estimated by the crop water use model (Fig. 17). In the present study, the estimation of water use by tomato plants grown in a greenhouse environment was made using the method proposed by Stanghellini (1987). As explained before, *ET* was estimated by multiplying the crop coefficient by ET_o. Thus, crop coefficients (K_c) were calculated as the ratio of these two (ET/ET_o). Crop coefficients were nearly equal to 1 ($K_c = 1.10 \pm 0.04$), indicating that *ET* was nearly equal to ET_o. These average midseason coefficients were similar to those found by Phene et al. (1985) and Hanson and May (2006) but smaller that found by Pruit et al. (1972).

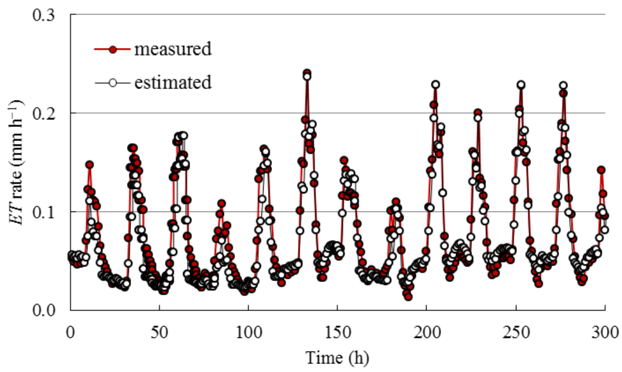

Fig. 17 Comparison between measured and estimated of hourly evapotranspiration (*ET*) rates during the observation time

The ET_o curve in Fig. 17 is slightly overestimated, which is thought to be due to the strong dependence of *Rs*, which can lead to error in the estimate. However, the differences are acceptable considering that the curve obtained by linear regression showed a good coefficient of determination ($P < 0.05$).

Information on crop use is essential for growers to provide an overview about the most effective way of sustaining crops, particularly in regions with water resource limitations. As shown in Fig. 17, the results indicate that the model estimated crop *ET*. In conclusion, the *ET* data calculated from the Stanghellini equation provided a good estimate of the values of actual *ET*.

Conclusions

The overall idea of the dissertation is to provide some information about the implementation of artificial intelligent techniques in order to give an overview in the development of intelligent control system, which can be applied on plant cultivation.

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