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Dynamic optimization of inside temperature of Zero Energy Cool Chamber for storing fruits and vegetables using neural networks and genetic algorithms

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ABSTRACT

A 'Zero Energy Cool Chamber (ZECC)' has been developed for storing fruits and vegetables from the viewpoints of low cost and energy savings. Adding water to a filler between the outer and inner brick walls and shade curtains is effective way to reduce the inside temperature of a ZECC. The objective of this study was to minimize the inside temperature by controlling the watering using an intelligent optimization technique (IOT) combined with neural networks (NN) and genetic algorithms (GA). The objective function was given by the average value of the inside temperature for one day. For dynamic optimization, the control process (24 h) was divided into 8 steps, and the optimal value (8-step ON–OFF intervals) of watering was obtained using NN and GA. In this method, dynamic changes in the inside temperature of the ZECC, as affected by the watering strategy, outside temperature and inside relative humidity conditions, were first identified using NN, and then the optimal value, which minimized the objective function, was determined through simulation of the identified NN model using GA. The average inside temperature for this optimal control was 4 °C lower than that for the continuous watering for 24 h, and was also 7.5 °C lower than that for no watering. The ZECC with the optimal watering strategy extended the shelf-life of tomato from 7 to 16 days. Thus, it was concluded that a ZECC optimized by using NN and GA is useful for storing tomato with no electric energy.

1. Introduction

A new ecofriendly storage system called the "Zero Energy Cool Chamber (ZECC)" has been developed from the viewpoints of low cost and energy savings. It is used for storing fruits and vegetables with no electric energy and has a simple structure consisting of outer and inner brick walls, a filler material between the brick walls, a half-ground storage space and a water supply system. A mixture of sand and zeolite was used as the filler to maximize the retention of the moisture within the filler. The inside temperature of the ZECC could be reduced by applying water to the filler (sand + zeolite) located between the brick walls using drip irrigation based on the principle of a passive evaporative cooling mechanism without requiring any electric energy. The water molecules in the filler between the brick walls evaporate under the influence of the outside unsaturated air through a cooling process that uses the latent energy of evaporation required for changing the physical state from liquid to vapor. During this process, the heat required for the water evaporation process is removed from the water, the filler and the brick walls creating a temperature of the inner wall of the ZECC lower than the dry-bulb temperature. The caloric energy is then removed from the fresh produce, and then the inside air of the ZECC due to heat transfer such as convection and conduction becomes lower along with the produce it contains. Therefore, it can be used for storing fruits and vegetables anywhere the ambient air is dry enough to create a significant temperature difference. Singh and Satapathy (2006) stated that throughout the year, relative humidity (RH) inside the ZECC was between 80% and 94%, whereas it varied between 70% and 83% under ambient conditions. Anyanwu (2004) indicated that the cool storage chamber temperature reduced from the ambient air temperature varied from 0.1 to 12 °C depending on the inside RH. Ganesan et al. (2004) reported that the shelf-life of brinjal could be extended up to 9 days in the cool chamber. Moreover, the weight loss and the rotting of fruit were reduced to about half during storage in the ZECC (Rajeswari et al., 2011).

Application of an optimization technique is effective for lowering and minimizing the inside temperature of the ZECC. For realizing this optimization, it is necessary to clarify the relationships between the input variables and the output variables. Solar radiation, outside temperature, watering and inside RH conditions are the main environmental factors that affect the inside temperature. In this study, however, the outside temperature, watering and

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inside RH directly influenced the inside temperature, therefore, they were used as input variables for identification and modeling. During a sunny day, the less humid outside air generates a strong drying force, and this enhances the evaporative cooling process from the wet filler of the ZECC and increases the difference between the outside air temperature and the inside temperature. On the other hand, during a rainy day, the high humid outside air failed to generate any drying force and thus significantly reducing the evaporative cooling efficiency. The outside RH is impossible to control is why this ZECC was operated during the dry season of the year when the overall average RH% was between 50% and 70%. As a result, the outside RH as a control input variable was not considered. However, the inside RH played a vital role in maintaining the freshness of tomatoes by preventing moisture loss and keeping the inside temperature lower for a longer period. This inside RH can be controlled by watering. It is well known that the output variable is the inside temperature of the ZECC. For optimal control, watering and the inside RH were used as the control inputs.

Intelligent approaches have emerged as promising techniques for effectively dealing with complex and/or ill-defined processes in agricultural production (Hashimoto et al., 2001). An IOT combined with NN and GA has been developed to optimize complex systems such as cultivating or fruit storage systems (Morimoto et al., 1997, 2003). NN is able to identify the nonlinear characteristics of a system with its own learning capability (Chen et al., 1990). McClendon et al. (1996) applied NN to predict the growth of peanuts and to achieve the optimal irrigation management. GA has the ability to rapidly search for an optimal global value of a complex objective function using a multi-point search procedure involving crossover and mutation (Goldberg, 1989). Therefore, the objective of this optimization was to find the optimal ON–OFF intervals of watering which minimizes the inside temperature of the ZECC.

The present study is an attempt to apply an IOT combined with NN and GA to realize minimization of the inside temperature of the ZECC by controlling the watering. In the method, dynamic changes in the inside temperature of the ZECC, as affected by the watering, the inside RH and outside temperature, are first identified using NN, and then an optimal watering operation that minimizes the inside temperature is determined through simulation of the identified NN model using GA. Finally, the optimal watering operation was applied to a real fruit storage process.

2. Materials and methods

The experiment was conducted at Ehime University, Matsuyama, from October 2010 to May 2012. To achieve the research objectives, three ZECCs were set up inside a greenhouse located at the Faculty of Agriculture, Ehime University. The recorded average room and water temperatures were respectively 25 °C and 20 °C, while the average wind speed was 0.5 m/s. A low speed wind tunnel was used to observe the relationship between the amount of watering and the air temperature. The fruit used for the experiment was the tomato (*Solanum lycopersicum* L. House-Momotaro). Total one hundred fifty tomato fruits were used for this experiment.

2.1. Structure of the ZECC

Fig. 1 presents the characteristics of the ZECC used during this study. The ZECC consisted of inner and outer walls made from bricks, a filler between the walls made of a mixture of sand (70%) and zeolite (30%), a storage space for the fruits or vegetables, a water supply system, and a shade curtain. The zeolite (Aedin, Natural activated zeolite, Honen No. 1, Size: 0.7 mm ϕ) was added to the sand in order to maintain the moisture of the filler as long as possible. The size of the ZECC is 1000 (L) × 900 (W) × 500 (H) mm. The 75 mm gap between the outer and inner walls was filled with a sand – zeolite mixture. A thermal insulating cover measuring 750 (L) × 650 (W) mm was used to cover the ZECC. A shade curtain measuring 1500 (L) mm × 1500 (W) mm with a 60% shading rate was also used to avoid direct exposure of the solar power and to lower the inside temperature of the ZECC. The shade curtain was always used in this experiment.

Tap water was supplied to the filler between the outer and inner brick walls through a low pressure micro sprinkler with a dimension of 97 (W) × 25 (D) × 188 (H) mm. The timing of the watering was controlled using a programmable electronic timer and was thus selected as the control input. The amount of watering was set to 45 L d − 1. Excessive water dripping from the ZECC was drained out.

2.2. Optimization problem

In general, a lower temperature is desirable to maintain the freshness of fruits and vegetables during storage. The environmental factors (control inputs) that affect the inside temperature of the ZECC are mainly solar radiation, outside temperature, watering, inside RH and the quality of the wall material of the ZECC. The shade curtain was always used in this experiment because it is a low cost method that significantly reduces the solar power. Of these factors, watering and inside RH were selected as the control input for optimization because they were the only controllable variable. For identification, three factors, outside temperature, watering and inside RH, were used as the input variables. Thus, a three-input (outside temperature, watering and inside RH) and one-output (inside temperature of the ZECC) system was adopted for identification.

The inside temperature of the ZECC usually decreases as the water supply to the filler increases. An excessive amount of watering (e.g., continuous watering) was not very effective for lowering the inside temperature. This is probably due to the decrease in the evaporation area caused by excessive water in the filler. It may also due to the fact that the water is likely at ambient temperature. For this cause, circulating much water would create a warming effect since the energy required for evaporation would be supplied be the excess of water circulation. Thus, an optimal amount of watering (=optimal watering operation) does exist for minimization of the inside temperature. In this study, the amount of watering was controlled by establishing the optimal ON–OFF interval for watering process.

Let $\mathrm{IT}(k)$ ($k = 1, 2, \ldots, N$) be a time series of the inside temperature of the ZECC as affected by the outside temperature $\mathrm{OT}(k)$, watering $\mathrm{W}(k)$ and inside RH $\mathrm{IH}(k)$ at time k. An objective function F (Eq. (1)) is given by the average value of the inside temperature for one day (Data number $N = 24\ \mathrm{h} \times 60\ \mathrm{min} = 1440$).

$$F = \sum_{k=1}^{k=N} \mathrm{IT}(k)/N \tag{1}$$

For optimization, the control process was divided into 8 steps. The sampling time is 60 s. Fig. 2 shows the watering operation characterized by the 8-step ON–OFF intervals $\mathrm{W}(k)$ which is a function of the ON–OFF intervals and given by the combination of 1 (ON) and 0 (OFF).

$$\begin{aligned} W(k) &= f_{onoff}(\text{ON—OFF intervals}) \\ &= f_{onoff}(T_1, T_2, T_3 T_4, T_5 T_6, T_7, T_8, T_9, T_{10}, T_{11}, T_{12}, T_{13}, T_{14}, \\ &\quad T_{15}, T_{16}) = \{1, \ldots, 1_{T1}, 0, \ldots, 0_{T2}, 1, \ldots, 1_{T3}, 0, \ldots, 0_{T4}, \\ &\quad 1, \ldots, 1_{T5}, 0, \ldots, 0_{T6}, 1, \ldots, 1_{T7}, 0, \ldots, 0_{T8}, 1, \ldots, 1_{T9}, \\ &\quad 0, \ldots, 0_{T10}, 1, \ldots, 1_{T11}, 0, \ldots, 0_{T12}, 1, \ldots, 1_{T13}, 0, \ldots, 0_{T14}, \\ &\quad 1, \ldots, 1_{T15}, 0, \ldots, 0_{T16}\} \end{aligned}$$

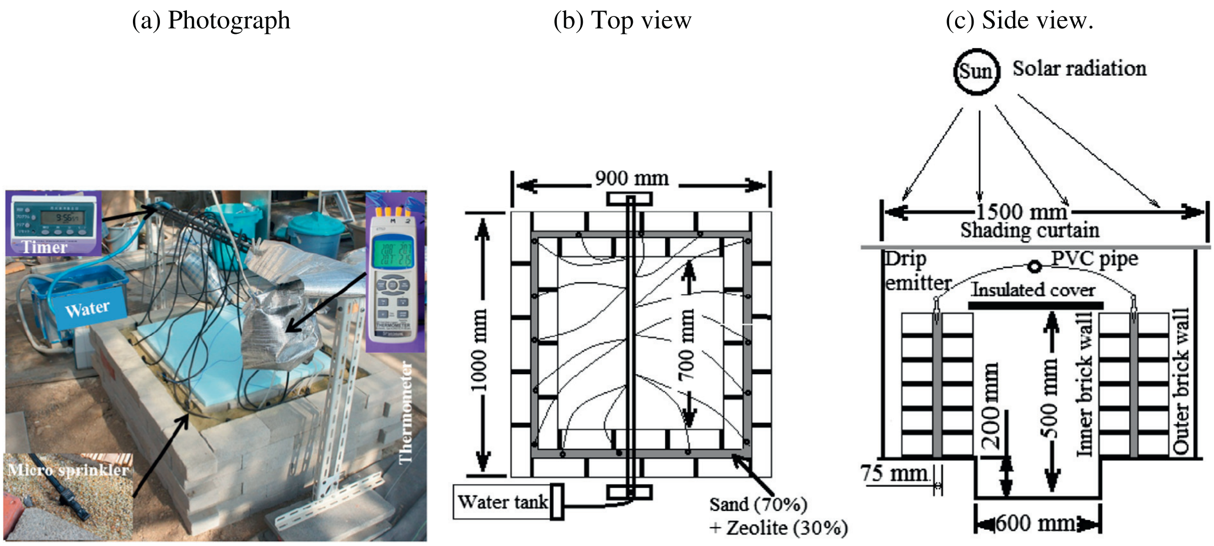

Fig. 1. Zero Energy Cool Chamber (ZECC): (a) photograph; (b) top view; and (c) side view of the system.

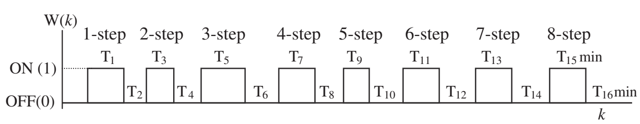

Fig. 2. The 8-step ON–OFF watering operation. The control input W(k) is given by {1, …, 1_{T1}, 0, …, 0_{T2}, 1, …, 1_{T3}, 0, …, 0_{T4}, 1, …, 1_{T5}, 0, …, 0_{T6}, 1, …, 1_{T7}, 0, …, 0_{T8}, 1, …, 1_{T9}, 0, …, 0_{T10}, 1, …, 1_{T11}, 0, …, 0_{T12}, 1, …, 1_{T13}, 0, …, 0_{T14}, 1, …, 1_{T15}, 0, …, 0_{T16}}(ON:1, OFF:0).

where f_{onoff} (.): a function that gives the lengths of ON (1) and OFF (0); ON times: T_1, T_3, T_5, T_7, T_9, T_{11}, T_{13}, T_{15}; OFF times: T_2, T_4, T_6, T_8, T_{10}, T_{12}, T_{14}, T_{16}.

Therefore, the optimization problem here is to determine the 8-step ON–OFF intervals of watering which minimize the objective function F. As for the constraint of the watering, the watering interval was restricted to 60 min or less in order to save water, easy drainage of excessive water and fit the real system.

$$\text{Minimizing } F \qquad (3)$$

Subjected to $0 \leqslant T_1, T_2, \ldots, T_{16} \leqslant 60$ min.

2.3. Dynamic optimization method

In this study, dynamic optimization was realized using an ICT combined with NN and GA (Morimoto et al., 2003). Fig. 3 shows the flowchart for determining the optimal value. In this technique, the dynamic response (diurnal change) of the inside temperature of the ZECC as affected by the watering and the outside temperature is first identified using NN, and then the optimal 8-step ON–OFF intervals for watering process which minimize the objective function F(W) are determined using simulation of the identified NN model and GA. Finally, the optimal value is applied to a real system.

2.4. Neural network for identification

A three-input (outside temperature, inside RH and watering) and one-output (inside temperature of the ZECC) system was used for identification. NN were used for identifying the dynamic response of the inside temperature of the ZECC as affected by the outside temperature, inside RH and watering, and for creating a

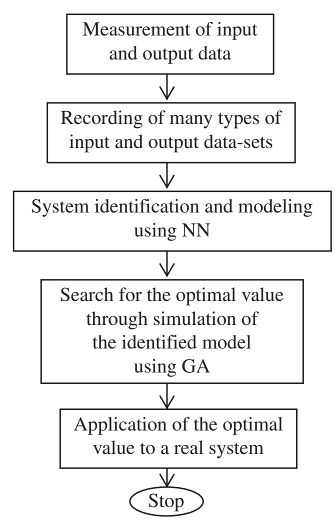

Fig. 3. Flowchart for determining the optimal value.

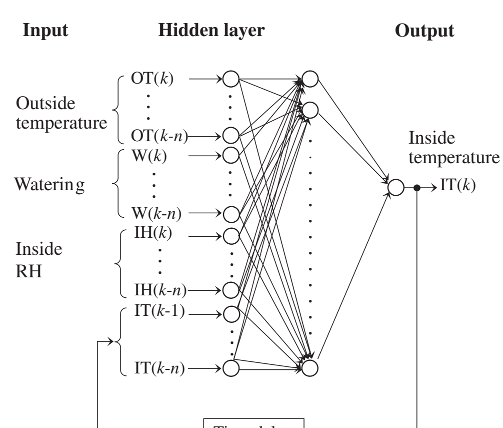

Fig. 4. A three-layered NN for identifying dynamic responses of the inside temperature IT(k), as affected by the outside temperature OT(k), watering W(k) and inside RH IH(k).

black-box model for simulation. Fig. 4 illustrates a NN time-delay for identifying the dynamic response of the inside temperature to outside temperature, inside RH (IH) and watering. It consisted of three layers and had arbitrary feedback loops that produce time histories of the input and output data for dynamic identification (Isermann et al., 1997). The input variables were the outside temperature OT(k) and watering W(k), IH(k), and the output variable was the inside temperature of the ZECC IT(k).

For the learning of the NN, two (n + 1)th historical input data, {OT(k), ..., OT($k-n$)} and {W(k), ..., W($k-n$)}, {IH(k), ..., IH($k-n$)} and one nth historical output data, {IT(k – 1), ..., IT($k-n$)}, are applied to the input layer, and one current output IT(k) is applied to the output layer as training signals (k = 0, 1, ..., $N-n$, N: data number) (Isermann et al., 1997). The learning method was error back-propagation (Rumelhart et al., 1986).

For the prediction, the current output, IT(k), was estimated from two (n + 1) th historical input data, {OT(k), ..., OT($k-n$)} and {W(k), ..., W($k-n$)}, {IH(k), ..., IH($k-n$)}and one nth historical output data, {IT(k – 1), ..., IT($k-n$)}, similar to an auto-regressive moving average (ARMA) model procedure (Isermann et al., 1997).

$$\mathrm{IT}(k) = f(\mathrm{OT}(k), \ldots, \mathrm{OT}(k-n), \mathrm{W}(k), \ldots, \mathrm{W}(k-n), (k), \ldots, \mathrm{IH}(k-n), \mathrm{IT}(k-1), \ldots, \mathrm{IT}(k-n)) \quad (4)$$

where n is the system order (system parameter number). The unknown function $f(\cdot)$ can be approximated by the NN.

2.4.1. Model validation

The data for identification were divided into two data sets, a training data set and a testing data set. The former was used for training the NN, and the latter was used for evaluating the accuracy of the identified model. The testing data sets had to be independent of the training data sets. An equal proportion was desirable for the number of the training and testing data sets. This type of model validation is called "cross-validation".

2.4.2. Choice of model structure

The most important task for determining the model's structure was the choice of the system parameter number. Here, the system parameter number and the hidden-neuron number of the NN were determined through trial and error based on the cross-validation. Twenty-three types of data sets for the input and output variables were divided into the training data set and the testing data set, and then identified using the NN. Twenty data sets were selected as the training data set for learning and three data sets as the testing data set for model validation.

2.5. Genetic algorithms for finding an optimal solution

Genetic algorithms were used for searching for determining the optimal 8-step ON–OFF intervals of watering that minimized the inside temperature of the ZECC. The imitation of a natural evolution process based on a crossing and a mutation provides a rapid search for an optimal value. Using the GA, an optimal value can be searched for in parallel with a multi-point search technique, rather than a single point procedure (Krishnakumar and Goldberg, 1992). Even if the objective function has many peaks, the multipoint search technique permits the focus of attention on the most valuable parts of the solution space and consequently, the global optimal value can be rapidly and efficiently sought from a very large search space (Hashimoto, 1997).

2.5.1. Definition of individual

In order to use the genetic algorithm, an 'individual' for evolution should be defined as the first step. Each individual represents a candidate for the optimal value. Since the optimal value is the 8-step ON–OFF intervals of watering, an individual can be given by the 8-step ON–OFF intervals of watering {T_1, T_2, ..., T_{16}}. They were all coded as 6-bit binary strings, which gives numerical values between 000000 (=2^0 – 1 = 0) and 111111 (=2^6 – 1 = 63 in decimal). The amount of watering as a value from 0 to 63 by using 6-bit binary strings. For optimization, however, the watering duration was restricted to 3600 s in order to save water and fit the real system (Eq. (4)).

$$\text{Individual } i = T_{i1}, T_{i2}, \ldots T_{i16} = \{000000, 111000, \ldots, 010101\}$$

A set of individuals is called a "population". They evolve toward better solutions. GA work with a population involving many individuals. The population size varies according to the use of genetic operations with a smaller population size tending to converge to the local optima. Local optima mean local optimization, not a global one. When an objective function is characterized by a complex function, a poor search technique sometimes falls into the local optima. A local optima does not allow obtaining a global (true) optimal solution.

2.5.2. Definition of fitness

Fitness is an indicator for measuring an individual's survival quality. All individuals are evaluated in terms of their performances, which is based on their fitness values. During the evolution process, individuals having a lower fitness reproduce, while individuals with a higher fitness die in each generation. An individual having the minimum fitness is regarded as the optimal solution. Fitness is similar to the objective function in conventional optimization problems. In this case, fitness can be defined as the objective function F given by Eq. (1).

$$\text{Fitness} = F = F(T_{i1}, T_{i2}, \ldots T_{i16}) \quad (5)$$

2.5.3. Genetic operations

Crossover and mutation were used as genetic operators. A single crossover was used. Two individuals (e.g., 000$\underline{110}$ and 101$\underline{101}$) are first mated at random. Next, these binary strings are cut at the 3-bit position along the strings and then two new individuals (000$\underline{101}$ and 101$\underline{110}$) are obtained by swapping all binary characters from the 1-bit to the 3-bit position. The mutation inverts one or more components of the binary strings from 0 to 1 or vice versa. Here, a two-point mutation was used. One individual (e.g., 0$\underline{1}$0$\underline{1}$10) is first selected at random, and then a new individual (0$\underline{0}$00$\underline{0}$10) is created by inverting two characters (genes), selected at random, from 0 to 1 or 1 to 0. The mutation operation increases the variability of the population and helps to avoid the possibility of falling into local optima in the evolution process (Krishnakumar and Goldberg, 1992). The number of mutations depends on the mutation rate. The selection of individuals was carried out based on the elitist strategy by which an individual with a maximum fitness must remain in the next generation. However, the searching performance can easily fall into a local optimum because only the superior individuals with the higher fitness are picked in each generation. In this study, therefore, quite different individuals (=100) in another population were added to the original population in order to maintain the diversity and obtain a global optimal value.

Fig. 5 shows the flow chart for determining the optimal value using the genetic algorithm. The procedure was as follows:

Step 1: As the first step, an initial population $P(0)$ consisting of N_i (=6) types of individuals was generated at random.
Step 2: N_o (=100) types of new individuals in another population were added to the original population to maintain the diversity of the original population. Both populations were independent of each other. This was applied to every generation.

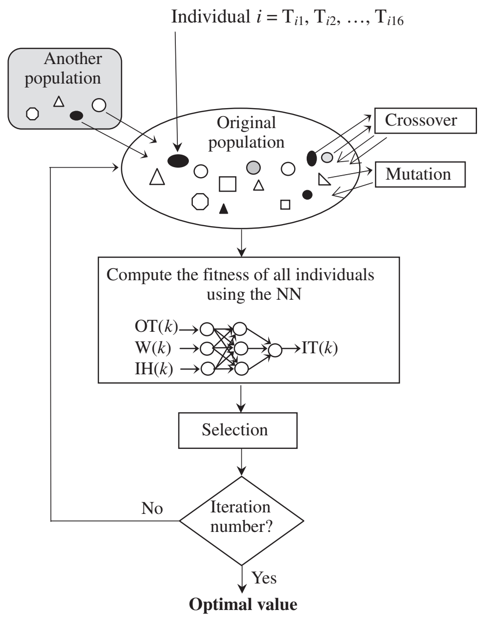

Fig. 5. Flow chart of the searching process for determining the optimal value using GA.

Step 3: Crossover and mutation operations were applied to the individuals selected at random and new individuals were generated. Through these operations, $N = N_i + N_o + N_c + N_m$ sorts of individuals were obtained (N_c and N_m represent individual numbers, newly created by the crossover and mutation, respectively).

Step 4: The fitness values {=*F*(individual)} of all individuals were calculated using the NN model, and their performances were evaluated.

Step 5: Superior individuals (=200) with lower fitness values were selected and retained for the next generation based on 'the elitist-strategy selection'.

Step 6: Steps 2–5 were repeated until fitness continues to generate the same minimum value with the increasing generation number. These operations were iterated until the optimal value was obtained. The optimal value was given by an individual with a minimum fitness.

2.6. Measurement of environmental factors and fruit quality

In order to investigate the dynamic responses of the inside temperature of the ZECC as affected by solar radiation, the outside temperature of the ZECC, watering, inside RH and their diurnal changes were measured. The external ambient temperature and inside temperature of the three ZECC were simultaneously measured using three digital thermometer (Sato Shoji, 47SD) with four thermocouples (0.3 mm) having an accuracy of ±0.5 °C. The relative humidity was measured using a thermohygrometer (Sato Shoji, HT-SD). The solar radiation was measured using a quantum flux density meter (UIZ3635 DC voltage datalogger). These data were recorded at the interval of 60 s for 24 h resulting in 1440 reading per day.

Physiological loss in weight (PLW, Eq. (5)) is one of the main factors in determining the quality of stored fruits and vegetables. Measurement of PLW and the shelf-life of the tomato were monitored every day using a digital electronic weight balance machine (BL-320S, Shimadzu Corporation, Japan). Since a decrease of only 5% in the PLW often results in a loss of freshness and wilted appearance (Ben-Yehoshua, 1987); the shelf-life of the tomato was determined based on a 5% PLW limit (Tarutani and Kitagawa, 1982).

$$Physio\log ical\ loss\ in\ weight, \% = \left[\frac{(X1 - X)}{X}\right] \times 100 \qquad (6)$$

where $X1$ = initial weight (g); X = weight (in units of g) at the end of the storage time.

The firmness of the fruit (kg cm^{-2}) was measured to evaluate the ripeness and deterioration of the tomato fruit during storage period using a fruit hardness tester (Fujiwara KM-1, Tokyo, Japan).

3. Results and discussion

3.1. Diurnal changes in the inside temperature of the ZECC for identification

First, many types of data-sets for the input and output variables were obtained for identification from a real system. Fig. 6a and b demonstrate typical diurnal changes in the solar radiation, the outside temperature, watering and the inside temperature and inside RH of the ZECC on sunny and rainy days, respectively. From the figure, it could be observed that the solar radiation first increased the outside temperature, and then the outside temperature increased the inside temperature. It was also observed that watering and higher inside RH significantly reduced the inside temperature. Twenty-three types of data sets of the inputs and the output were obtained for identification.

During a sunny day, the average outside temperature was 30.7 °C under a shaded condition. On a rainy day, however, it was 25.7 °C because of the lower solar radiation rate reaching the storage room. Under a watering and shaded condition during a sunny day, the average inside temperature of the ZECC was recorded to be 20.6 °C, while during a rainy day, it was 21.5 °C. Therefore, during a sunny day under the watering and shaded condition, the maximum average outside and inside temperature difference was 10.0 °C, while during a rainy day, this difference was only 3.6 °C. This is because the outside temperature around the ZECC and the vapor pressure of the moist sand and zeolite mixtures and the surrounding air tend to equalize. Liquid water molecules in the moist sand and zeolite mixtures evaporate under the influence of the outside air through a process that uses energy to change the physical state. Heat moves from the higher temperature of the air and brick walls to the lower temperature of the water due to convection and conduction. During this conversion process, the surrounding temperature decreased. This cooling temperature by the effect of evaporation cools the inside temperature of the ZECC below the dry-bulb temperature. On the other hand, shade curtain blocked 60% of the solar radiation by preventing the direct exposure of solar radiation to the surface of the ZECC which increased the inside temperature of the ZECC. Therefore, it was found that the combination of higher outside temperature, watering, inside RH and shade curtain provide the lowest inside temperature of the ZECC.

3.2. Relationship between the amount of watering and the inside temperature

The effect of the amount of water used on the inside temperature was also investigated. Fig. 7 shows the fundamental relationship between the amount of watering of the sand and the air temperature at 10 mm over the sand in a wind tunnel. A wind velocity of 4 mm/s was used. The air temperature decreased with the increase of the amount of water used. Fig. 8 illustrates the actual relationship between the amount of watering and the inside temperature of the ZECC. In this case, we had three levels of water-

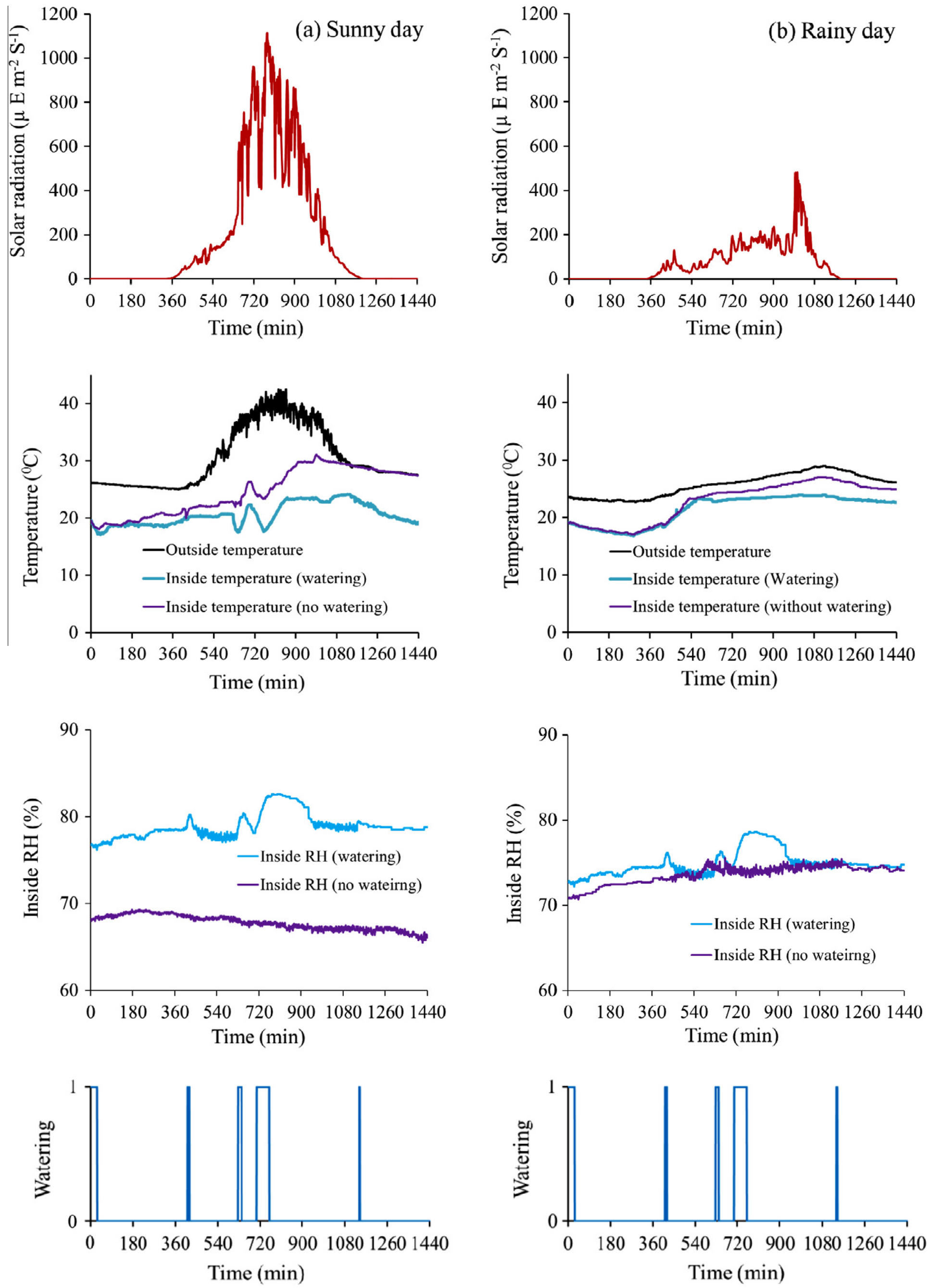

Fig. 6. Diurnal changes in solar radiation, outside temperature and inside temperature and RH in the ZECC under shading and watering conditions.

ing (30, 45 and 60°L d – 1). The minimum inside temperature of 19.7 °C was achieved by the intermediate watering of 45 L d – 1, not the 30 and 60 L d – 1watering. From these two figures, it was found that increasing too much the amount of water does not minimize the inside temperature, and the optimal amount of watering does exist for its minimization. This is because the presence of an excessive amount of water in the filler lowered the evaporation rate due to the decrease of the porous area inside it. The suitable moisture condition of the filler in the brick wall can more effectively minimize the inside temperature than the excessive moisture condition. Thus, it is necessary to optimize the amount of watering to improve the maximum cooling performance of the ZECC. We optimized the ON–OFF intervals of watering instead of the amount of watering for minimizing the inside temperature.

3.3. Determination of system order and hidden neuron number

Next, some parameters of the model-building of the NN were determined. The effect of the system order on the accuracy of the estimation was first investigated. Fig. 9 shows the relationship between the system order n and the estimation error (root mean square error: RMSE). It was found that the RMSE value decreases as n increases. The 70th was selected as the effective system order because it gave the minimum RMSE value.

Second, the effect of the neuron number in the hidden layer on the accuracy of the estimation was investigated. Fig. 10 shows the relationship between the neuron number in the hidden layer N_h and the RMSE. The neuron number was changed between one and nine. The minimum value of the RMSE was obtained when

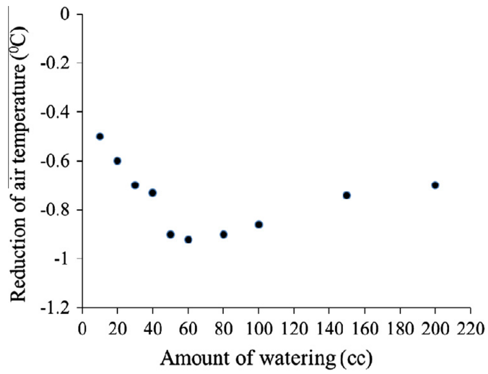

Fig. 7. Fundamental relationship between the amount of watering and the air temperature at 10 mm over the sand in a wind tunnel test. The wind velocity was 4 mm/s.

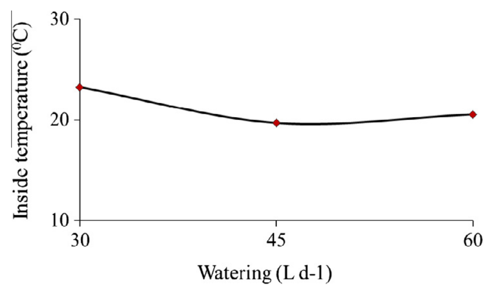

Fig. 8. Relationship between the amount of watering (30, 45 and 60 L d – 1) and the inside temperature of the ZECC.

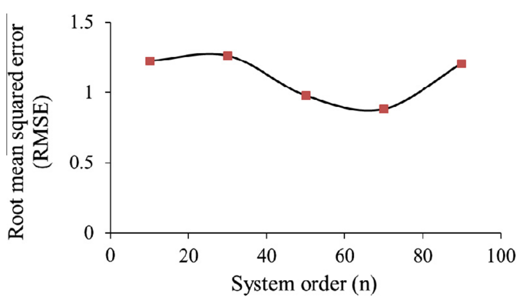

Fig. 9. Relationship between the system order and the root mean squared error (RMSE) during a fine day.

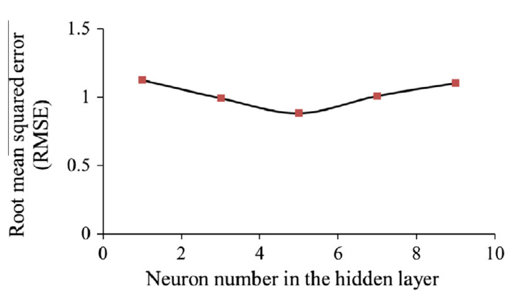

Fig. 10. Relationship between the neuron number in the hidden layer and the root mean squared error (RMSE) during fine day (45 L d – 1).

the neuron number was five. Therefore, the 5th neuron number in the hidden layer was chosen as the optimal neuron number.

From Figs. 8 and 9, it was concluded that the system order $n = 70$ and the neuron number in the hidden layer $N_h = 5$ are effective for identification.

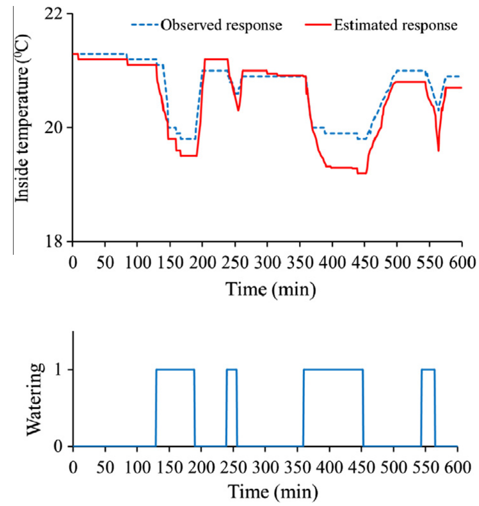

Fig. 11. Comparison of the estimated and observed responses of the inside temperature to watering process.

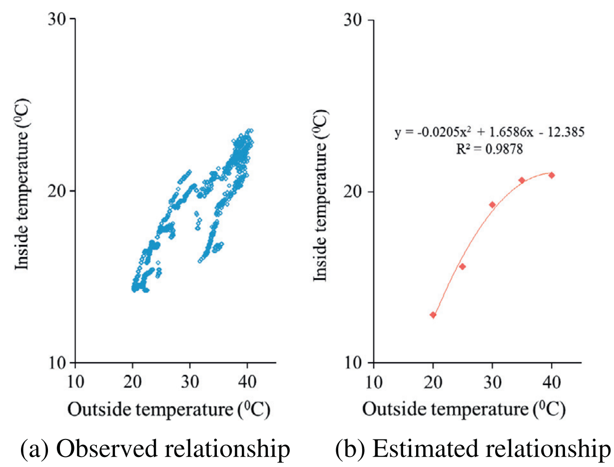

Fig. 12. Comparion of the static relationship between the outside temperature and the inside temperature of the ZECC on a fine day.

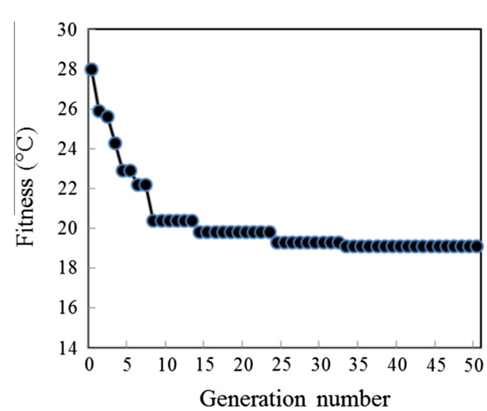

Fig. 13. Evolution curve in searching for the optimal value using the genetic algorithm.

3.4. Identification results

In order to confirm the model accuracy, the dynamic response (short-term diurnal change) of the inside temperature was com-

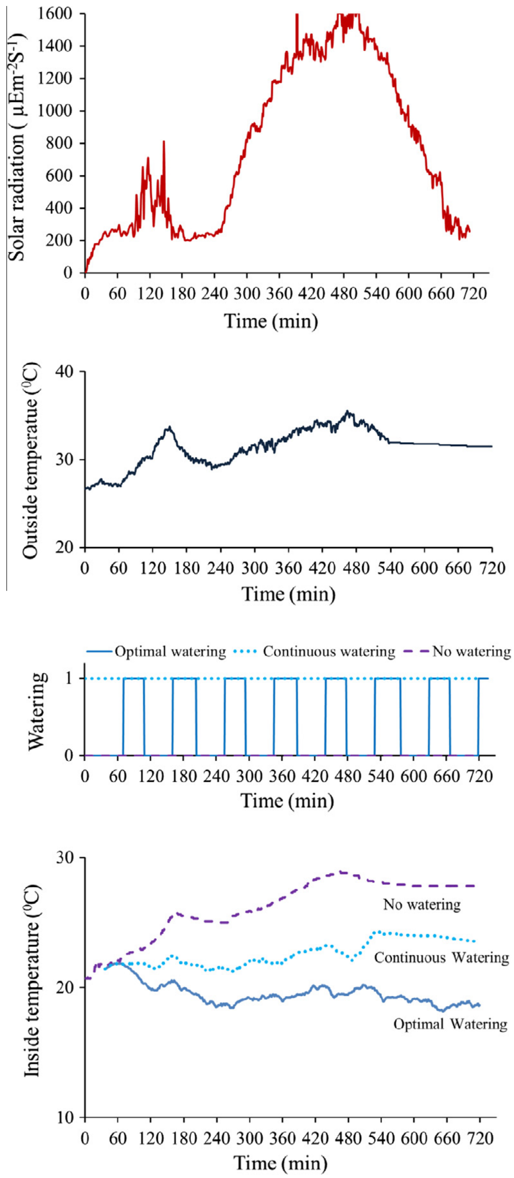

Fig. 14. The optimal control performance of the inside temperature of the ZECC by the control of the optimal watering based on optimal ON–OFF watering intervals.

pared between the estimated and real responses. Fig. 11 is a comparison of the dynamic response of the inside temperature as affected by the watering and the outside temperature of the ZECC on a fine day. These testing data were independent of the training data. The solid line shows the estimated response obtained from the NN model and the broken line shows the observed one. From the figure, it was found that the estimated response was closely related to the observed one.

Next, the static relationship between the outside temperature, which depends on the solar radiation, and the inside temperature of the ZECC was investigated. Fig. 12 shows the comparison of the observed relationship (a) and the estimated relationship (b) between the outside temperature and the inside temperature of the ZECC. In this case, the other input variable, watering, was maintained at 0 (no watering). The estimated relationship was obtained from a simulation of the NN model. All the data in this graph were obtained from the calculation of the step responses of the inside temperature as affected by various levels of the step input of the

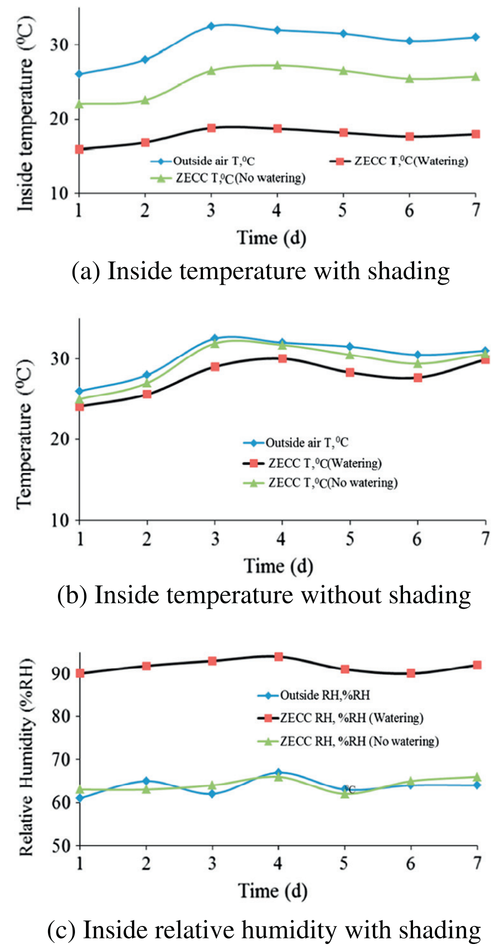

Fig. 15. Daily changes in the inside temperature and relative humidity of the ZECC with the optimal watering for 7 days.

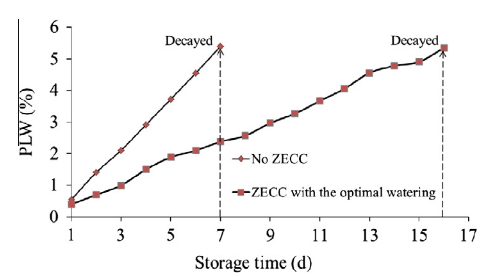

Fig. 16. Physiological loss in weight of tomato stored at room temperature outside the ZECC, versus stored inside the ZCC with optimal watering.

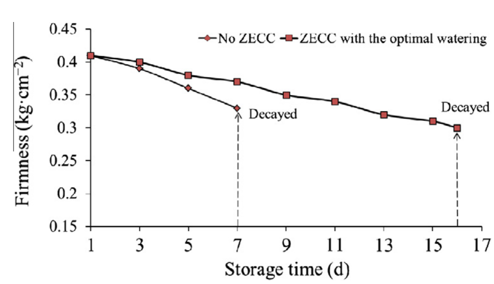

Fig. 17. Changes in firmness of tomato stored at room temperature and inside the ZECC with optimal watering.

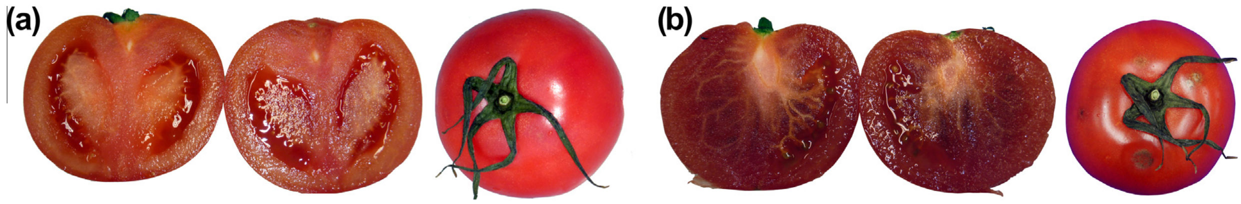

Fig. 18. Visual appearances of tomatoes (a) after 16 days of storage inside the ZECC with optimal watering, and (b) after 7 days of storage at room temperature.

outside temperature. It can be seen that the estimated relationship was closely related to the observed one.

In general, it is well known that the relationship between the outside temperature and the net inside temperature show nonlinear characteristics due to the thermophysical properties of the cooling wall and environmental factors (Zhang et al., 2008). The nonlinear characteristics appear in both curves. This implies that the nonlinear identification of the net inside temperature was well attained using the NN method. These results suggest that a reliable computational model could be obtained for predicting the behavior of the inside temperature under any combination of watering.

3.5. Optimal control results

3.5.1. Optimal value obtained from the genetic algorithm

Fig. 13 shows evolution curves in searching for an optimal value using the genetic algorithm. The crossover and mutation rates were 0.8 and 0.5, respectively. The selection technique was based on an elitist strategy which retains an individual with a maximum fitness for the next generation in each generation. From the curve, the fitness (the value of objective function) dramatically increased with the generation number and then reached the maximum value. The searching procedure is usually stopped when the fitness continues to have the same maximum value with the increasing generation number, and an optimal value can be given by an individual with this maximum fitness. The optimal value was obtained at the 33rd generation. The searching performance can easily fall into a local optimum because only the superior individuals with the higher fitness are picked in each generation. In this case, a global optimal value could be successfully obtained by increasing the diversity of the original population by adding very different individuals from another population. The obtained optimal value was T_1 = 35 min ON, T_2 = 55 min OFF, T_3 = 35 min ON, T_4 = 55 min OFF, T_5 = 35 min ON, T_6 = 55 min OFF, T_7 = 35 min ON, T_8 = 55 min OFF, T_9 = 35 min ON, T_{10} = 55 min OFF, T_{11} = 35 min ON, T_{12} = 55 min OFF, T_{13} = 35 min ON, T_{14} = 55 min OFF, T_{15} = 35 min ON, and T_{16} = 55 min OFF. The confirmation of the optimal value was carried out using a round-robin algorithm.

3.5.2. Optimal control performance of the inside temperature

Fig. 14 illustrates the optimal control performance of the inside temperature of the ZECC as affected by the optimal watering, obtained from simulation for 12 h, under the shaded condition. The solid, broken and dash lines show the cases of the optimal watering, continuous watering and no watering, respectively. The other input variable, solar radiation, was maintained constant at the adequate observed diurnal change during the simulation. The average values of the inside temperature were 18.7, 22.6 and 26.2 °C for the cases of the optimal watering, continuous watering and no watering. Thus, the inside temperature for the optimal watering was 4 °C lower than that for the continuous watering, and 7.5 °C lower than that for no watering. This is probably because the optimal watering provided a suitable balance of the gas and liquid phases for the active evaporation.

3.5.3. Application of the optimal watering operation for real fruit storage

Next, the optimal value (optimal ON–OFF intervals of watering) was applied to a long-term real fruit storage. Fig. 15 illustrates the daily change in the average inside temperature and relative humidity of the ZECC over seven days when using the optimal value of watering. From (a), under the shaded condition, the optimal watering lowered the average inside temperature to 18 °C, while no watering increased it to 25.4 °C. However, from (b), with no shade curtain, the inside temperature increases even if watering is optimally conducted. From (c), the average values of the inside relative humidity with the optimal watering and no watering were 91.7 and 64.1%RH, respectively, under the shaded condition.

Finally, the quality of the fruit and vegetables were investigated during the optimal watering.

Fig. 16 is a comparison of the daily changes in the PLW of tomatoes stored inside the ZECC with optimal watering and outside the ZECC (room temperature). The optimized ZECC reduced the PLW percentage of the tomatoes when compared to those stored outside the ZECC. After 7 days, the PLW of the tomatoes stored at room temperature and in the ZECC was respectively 5.4% and 2.3%. The PLW of tomatoes stored in the optimized ZECC reached 5.33% after 16 days. Thus, the PLW of tomatoes inside the ZECC was lower than those stored outside the ZECC.

Fig. 17 shows a comparison of the daily changes in the firmness of the tomatoes stored inside the ZECC with the optimal watering and outside the ZECC (room temperature). In general, the firmness of the fruit decreased and softened more rapidly when stored at room temperature then when stored in th ZECC. The tomatoes stored in the ZECC with optimal watering softened with time from 0.41 to 0.30 kg cm^{-2} and decayed at 16 days, while those stored at room temperature softened to 0.33 kg cm^{-2} and spoiled at 7 days. Ball (1997) suggested that a postharvest change in firmness can occur due to the loss of moisture through transpiration, as well as enzymatic changes. In addition, the hemicelluloses and pectin become more soluble, which resulted in disruption and loosening of the cell walls (Paul et al., 1999).

Fig. 18 shows the visual appearances of the tomatoes after storage in the case shown in Fig. 17. In this figure, (a) is the tomatoes stored in the ZECC with optimal watering for 16 days and (b) are those stored at room temperature for 7 days. It is found that a significant decay was observed in the tomatoes stored at room temperature for 7 days, while the tomatoes stored in the ZECC with the optimal watering for 16 days appeared to have only a small decay on the fruit. Microorganisms easily infect the tomatoes and uncontrolled ethylene production causes the fruits to ripen faster. However, the ZECC with the optimal watering produced a lower inside temperature and then delayed the softening and decay of the fruit.

Thus, it was determined that the ZECC with the optimal watering is useful to store fruit and vegetables with no electric energy.

4. Conclusion

The inside temperature of the ZECC as affected by climate factors is quite complex and uncertain. In this study, an intelligent optimization technique combined with neural networks and genetic algorithms was applied to minimize the inside temperature of the ZECC. The control input was watering which is supplied to the filler made from sand and zeolite between the brick walls. First, the inside temperature of the ZECC as affected by the outside temperature, watering and inside RH was identified using the neural network. A three-layered neural network with a time-delay operator was useful for identifying this dynamic system. Then, the genetic algorithm was used for searching for the optimal 8-step ON–OFF intervals of watering which minimize the inside temperature of the ZECC through simulation of the identified neural-network model. High diversity of the population by adding some individuals from another population and having high crossover and mutation rates shortened the searching time for the global optimal value. The optimal intervals obtained for the watering schedule were T_1 = 35 min ON, T_2 = 55 min OFF, T_3 = 35 min ON, T_4 = 55 min OFF, T_5 = 35 min ON, T_6 = 55 min OFF, T_7 = 35 min ON, T_8 = 55 min OFF, T_9 = 35 min ON, T_{10} = 55 min OFF, T_{11} = 35 min ON, T_{12} = 55 min OFF, T_{13} = 35 min ON, T_{14} = 55 min OFF, T_{15} = 35 min ON, and T_{16} = 55 min OFF. The average inside temperature for this optimal control was 4.0 °C lower than that for the continuous watering for 24 h, and was also 7.5 °C lower than that for no watering. Furthermore, the shelf-life of the tomatoes during storage in the optimized ZECC was extended from 7 to 16 days. Thus, it is concluded that the ZECC storage system optimized with an intelligent optimization technique combining with the neural network and genetic algorithm achieves a minimum inside temperature and is therefore effective for storing tomato from the viewpoints of low cost and energy saving.

Acknowledgments

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