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OPTIMAL CONTROL OF THE WATER LOSS OF FRUIT DURING STORAGE BY HEAT STRESS

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Abstract: In general, lower temperature is useful to reduce the quality losses of fruit. In contrary, a short-term exposure to high temperature between 35 and 50°C allows the ripening of fruit to delay. In this study, the optimal *l*-step set points of temperature that minimize the water loss of the fruit were determined using a decision system consisting of neural networks and genetic algorithms and applied to a real system. In the decision system, the dynamic change in the rate of the water loss, as affected by temperature, was first identified using neural networks, and then the optimal *l*-step set points of temperatures that minimize the rate of the water loss were sought through simulation of the identified model using genetic algorithms. Several types of optimal values were obtained under different constraints of the temperature and evaluation lengths of the control process. Especially, a temperature operation first rising to the highest level and then dropping to the lowest level in the given range was effective to reduce the water loss than that keeping it constant at the lowest level through whole the control process.

Keywords: Optimal control, fruit-storage process, water loss, heat stress, temperature, neural networks, genetic algorithms

1. INTRODUCTION

Storage temperature for fruits is usually controlled at low level. It is also maintained constant. This is because the low temperature is effective to reduce the microbial spoilage and water loss of the fruit. In recent years, however, researchers have demonstrated that a heat treatment (a single heat stress) between 35 and 50°C is effective to inhibit ethylene production and delay the ripening of fruit (Biggs *et al.*, 1988; Lurie and Klein, 1991 and 1992; McDonald and McCollum, 1996). An intermittent heat stress is also more effective than a single one in delaying the ripening of fruit (Morimoto *et al.*, 1997; Artés *et al.*, 1998a and 1998b). It is also reported that heat treatment can maintain better firmness of fruits (Tu and De Baerdemaeker, 1996).

It is well known that the exposure of living organisms to heat stress produce several types of heat shock proteins (HSPs) in their cells and acquire transient thermo tolerance (Kimpel and Key, 1985). Acquiring the thermo tolerance may lead to the reduction of the water loss for fruits during storage. So, it is important to know how we apply the heat stress to the fruit

For realizing the optimal control, measurement and identification of the physiological responses of the fruit (fruit responses) are essential. The rate of the water loss is a major fruit response for evaluating quality losses for fruits. It allows non-destructive and continuous measurement. A reduction of the water loss leads to a longer maintenance of the fruit quality. In general, however, it is difficult to apply optimal control techniques to the reduction of the water loss during storage because the physiological behaviors between the temperature (heat stress) and the water loss are quite complex and uncertain.

Intelligent approaches such as neural networks and genetic algorithms make the treatment of complex systems easier. Neural networks are useful for identifying complex nonlinear systems (Chen, *et al.*, 1990). Genetic algorithms can find an optimal value of a complex problem successfully. It searches for an optimal value with multi-point procedure by simulating the biological evolutionary process (Goldberg, 1989). An intelligent control technique consisting of neural networks and genetic algorithms has been developed for the optimization of complex systems in plant and fruit factories (Morimoto *et al.*, 1995, 1996 and 1997).

The aim of this study is to determine the optimal *l*-step set points of temperature that minimize the water loss of the fruit using a decision system consisting of neural networks and genetic algorithms and applied them to the real control system. The control input is temperature, and the control output is the rate of the water loss for the fruit.

2. SPEAKING FRUIT APPROACH (SFA)

In the most commonly used storage technique for fruits, the environmental factors are maintained constant (e.g., lower temperature), without any considerations of the physiological status of the fruit. For the purpose of the qualitative improvement of the fruit, however, it is essential to control the environment flexibly and optimally, taking the physiological status of the fruit into consideration. Measurement of the fruit responses and the control based on their information are important in order to realize the optimal control. The storage environment for fruits is controlled optimally based on the fruit responses at that time. This approach is explored as a "speaking fruit approach (SFA)" (De Baerdemaeker and Hashimoto, 1994).

Figure 1 shows the schematic diagram of the concept of an SFA-based control for fruit-storage process. It consists of a sensor to measure the physiological responses of the fruit (fruit responses), a computer to determine the optimal set points of the environment and control devices to control the environment at the optimal set points. A kind of real-time control technique is applied to the fruit-storage process.

3. OPTIMAL CONTROL PROBLEM

3.1. Fruit material

Tomato fruits (*Lycopersicon esculentum* Mill. cv. Momotaro) were used for the experiment. Mature green tomatoes of uniform size (about 8 cm in diameter) were stored in a storage chamber (Tabai-espec, LHU-112M), where the temperature and relative humidity can be controlled with the accuracy of ±0.1°C and ±2%, respectively. Three tomatoes were used for each experiment. The rate of the water loss of the tomato was estimated from the weight loss. The fruit weight was measured by hanging some fruits from an electric balance (Sartorius, LP-620S), which was put outside of the chamber. The sampling time was 10 minutes.

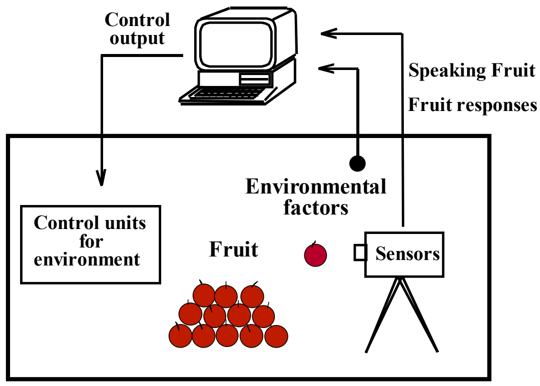


Fig. 1. An SFA-based control system for fruit-storage process

3.2. Optimal control problem

The aim for optimal control is to reduce the rate of the water loss of the tomato as much as possible. Let $W_T(k)$ (k=1, 2, ..., N) be time series of the rate of the water loss, as affected by temperature T(k), at the time k. An objective function, F(T), was given by the reciprocal number of the function P(T), derived from the sum of values at the last stage ($k=N_L$, ..., N) in the control process (N_L: starting time point at the last stage, N: final time point).

$$P(T) = \sum_{k=N_L}^{N} W_T(k) / (N-N_L+1) \qquad (1)$$

$$F(T) = 1 / P(T) \qquad (2)$$

P(T) is the average value of the summation of the rate of the water loss at the last step ($N_L \leq k \leq N$). It is noted that, in this study, the rate of the water loss at only the last step in the control process was evaluated. The reason that we make it a reciprocal number is only due to the transformation from the minimization problem to maximization one in order to fit the genetic evolution.

The control process was divided into *l*-step Hence, the optimal control problem here is to determine the *l*-step set points of the temperature, which maximize the objective, function F(T). As for the constraint of the temperature, five types of temperatures (T_{min} = 5, 10, 15, 20, or 25) were given as the minimum temperature while the maximum temperature was fixed to 40°C.

$$\text{maximize } F(T)$$
$$\text{subject to } T_{min} \leq T(k) \leq 40°C$$

4. DESIGN OF AN INTELLIGENT OPTIMAL CONTROL SYSTEM FOR SFA

4.1 An SFA-based intelligent optimal control system

Figure 2(a) shows the block diagram of an SFA-based intelligent control system for realizing the optimal control of the rate of the water loss. It consists of a decision system and a conventional feedback control system. The decision system consists of neural networks and genetic algorithms. The neural network is used for identifying the rate of the water loss, as affected by temperature, and the genetic algorithm for searching for an optimal value (l-step set points of temperature which maximize the objective function) through simulation of the identified model. Identification and the search for an optimal value are periodically repeated to adapt the time-variation of the physiological status of the fruit..

4.2 Neural network for identification

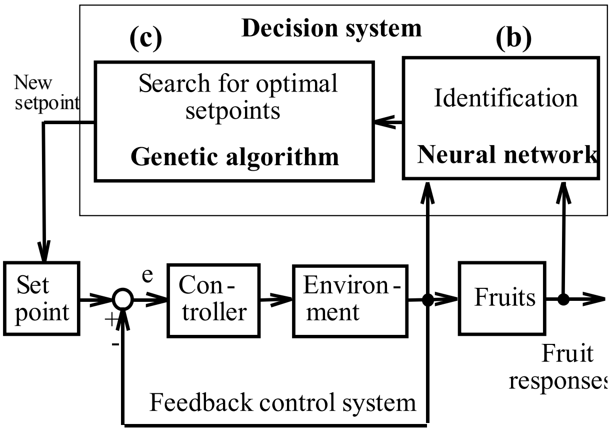
Figure 2(b) shows the structure of a three-layer neural network used for identification. Historical input and output data through time-delay operators are used for describing the dynamic property of the system. The learning way was error back-propagation (Rumelhart et al., 1986). The system order and the hidden-neuron number of the neural-network were determined based on the cross-validation.

4.3. Genetic algorithm for finding an optimal value

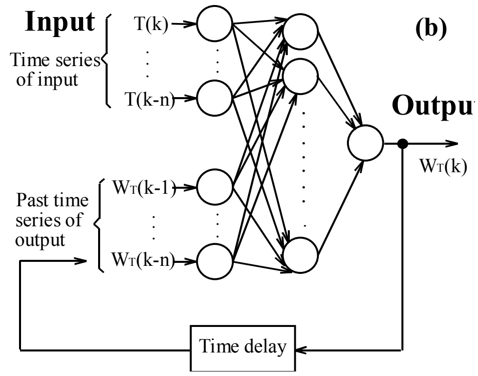
Since the control process consists of l-steps, an individual was given as l-step set points of temperature $\{T_1, T_2, \ldots T_l\}$ and they were all coded as a 6 bit binary strings. Figure 2(c) shows the definitions of the individual and the population. 1) Initial population consisting of N_i (=6) types of individuals is generated at random. 2) N_o (=50) types of individuals are added to the original population from another population. 3) Crossover and mutation operators are applied to those individuals. Through the crossover and the mutation, N_c and N_m sorts of individuals are newly created. 4) The fitness of all individuals is calculated using the identified neural-network model. 5) N_r (=200) individuals with higher fitness are selected and retained for next generation. An optimal value can be obtained by repeating these procedures.

5. MEASUREMENT AND IDENTIFICATION

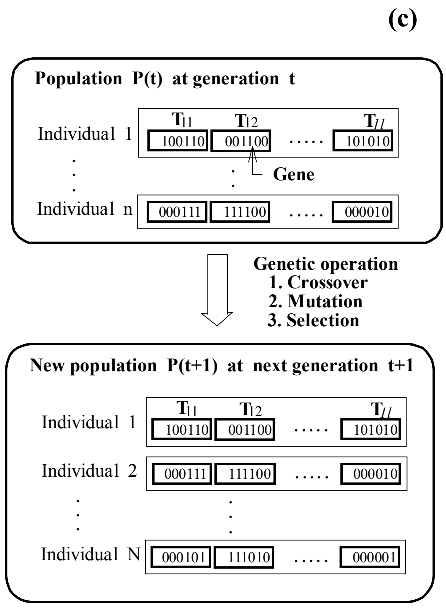
Figure 3 shows eight types of dynamic changes in the rate of the water loss for about 192 hours, as affected by temperature. For obtaining better identification, the temperature was flexibly changed between 5 and 40°C. Short-term heat stresses of 40°C for about 24 hours were included in several control inputs. Each data has different data number. The sampling times in all cases are ten minutes. From the figure, it is found that the rate of the water loss significantly varied in relation to the temperature.



(a) An intelligent control system



(b) A three-layer neural network for identification



(c) Definition and cording of individuals

Fig. 2. An SFA-based intelligent control system for realizing the optimal control of the storage process.

Next, all the data in Fig.3 (training data set) were identified using the neural network to make a model. The number of system parameter and the hidden neuron number of the neural network were respectively determined to be n=20 and n_h=20 through cross-validation. Figure 4 shows the comparison of the estimated response and the observed response for the rate of the water loss. A testing data set was used for this comparison. It was found that the estimated response was closely related to the observed one. This means that a simulation model to find an optimal value could be obtained.

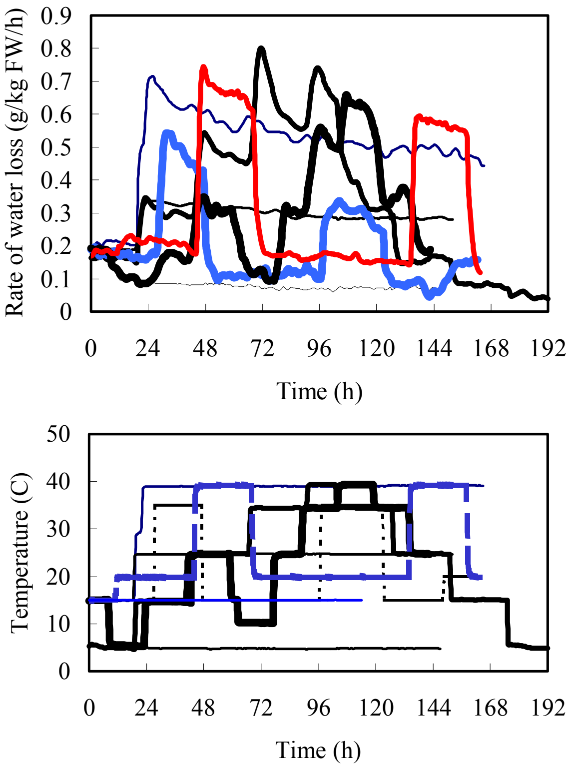


Fig. 3. Eight types of dynamic changes in the rate of the water loss, as affected by temperature

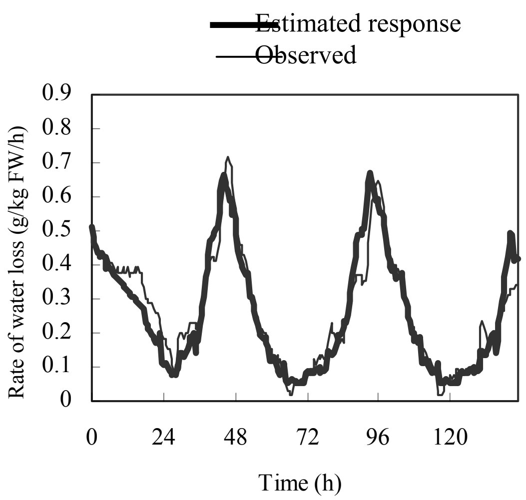


Fig. 4. Comparison of the estimated and observed responses of the rate of the water loss.

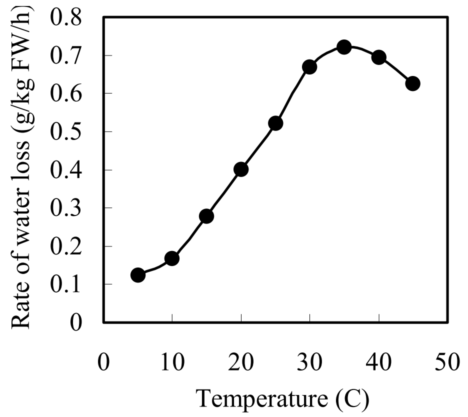


Fig. 5. Relationship between the temperature and the rate of the water loss (simulation results).

Figure 5 shows the estimated static relationship (regression curve) between the temperature and the rate of the water. All data plotted in the figure were obtained from simulation of the identified neural-network model. The rate of the water loss increased with temperature. It showed a significant non-linearity. Over 35°C, it can be seen that the rate of the water loss was significantly suppressed by the heat stress.

6. OPTIMAL CONTROL PERFORMANCES

6.1 Search for an optimal value

For realizing the optimal control, the control process was divided into l (=10)-step, and an optimal value (l-step set points of the temperature) was searched for through simulation of the identified neural-network model, using the genetic algorithm. Several types of optimal values (l-step set points of the temperature) were obtained from simulation under different constraints of the temperature and evaluation lengths of the control process. The optimal values obtained here depended on the constraint of the temperature and the evaluation length of the control process. When the constraint was $15 \le T_l \le 40$°C and the evaluation length was the latter half stage of the control process, T_l ={40, 40, 15, 15, 15, 15, 15, 15, 15, 15°C}, which contains a single heat stress, was selected as an optimal value. On the other hand, T_l ={40, 40, 15, 15, 40, 40, 15, 15, 15, 15°C}, which contains double heat stresses, was chosen as an optimal value when the evaluation length was the last stage of the control process and the constraint was $15 \le T_l \le 40$°C.

Under the constraint of $5 \le T_l \le 40$°C, on the other hand, an optimal value was given by the combination of only the lowest temperature, T_l ={5, 5, 5, 5, 5, 5, 5, 5, 5, 5°C}. This control manner was the same as a conventional control one.

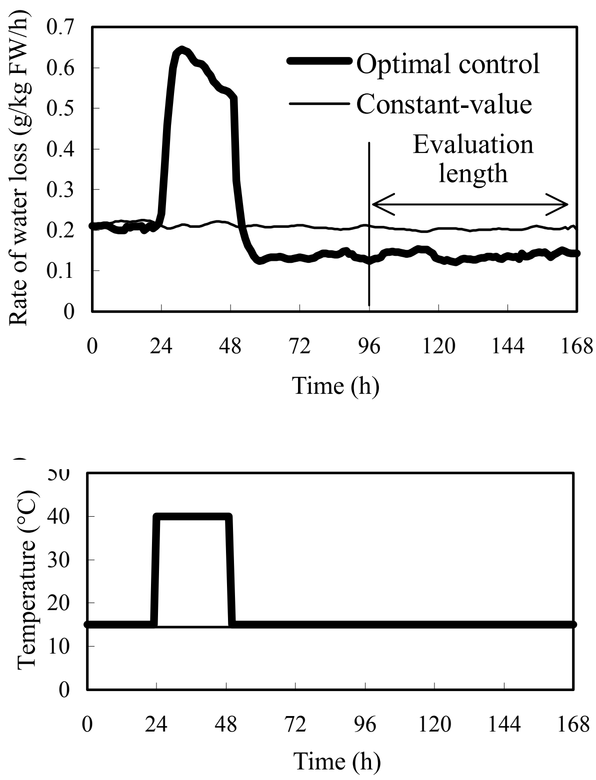


Fig. 6 An optimal control performance of the rate of the water loss of the fruit when the evaluation length is the latter half stage of the control process (96 to 168 h) under the temperature range (15≤ T(k)≤40°C).

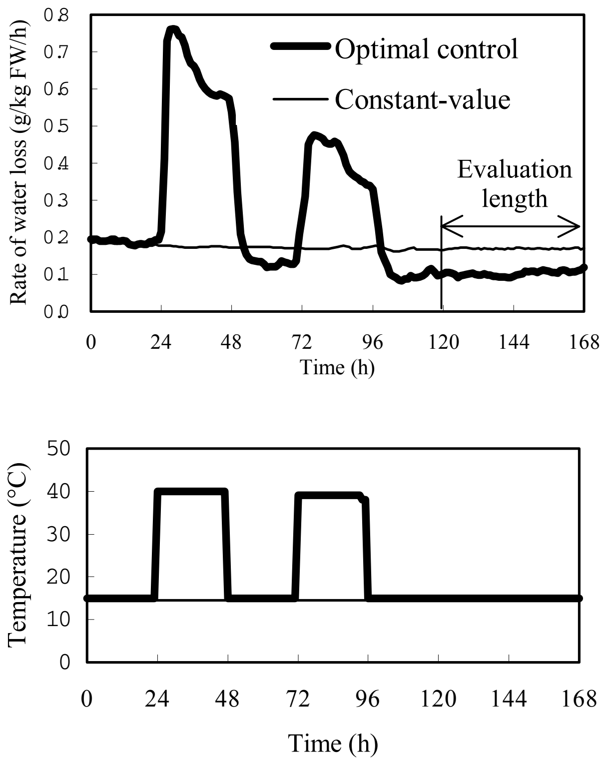


Fig. 7. An optimal control performance of the rate of the water loss of the fruit when the evaluation length is final stage (last two stages) of the control process and the temperature range is (15≤ T(k)≤40°C).

6.2 Actual control performances

Finally, several types of optimal values (single and double heat stresses) obtained from simulation were applied to a real storage system. Figure 6 shows an optimal control performance of the rate of the water loss when an optimal value (a single heat stress) was applied to the fruit. In this case, the evaluation length is the latter half stage of the control process, and the constraint of the temperature is 15 ≤ T ≤ 40°C. It is found that, after the single heat stress application, the rate of the water loss becomes lower in the optimal control than in the constant-value control.

Figure 7 shows an optimal control performance of the rate of the water loss when an optimal value (double heat stresses) was applied to the fruit. In this case, the evaluation length was the final stage (last two stages) of the control process, and the constraint was 15 ≤ T ≤ 40°C. It is found that the rate of the water loss in the optimal control decreases every applying the heat stress and, after the double heat stresses, its value becomes much lower than that in the constant-value control during the final stage. It is also found that the values of the rate of the water loss during the second heat stress application are much lower than that during the first heat stress application. This is because the first heat stress significantly suppressed the water loss of the fruit. These results suggest that the stored fruit acquired a transient thermo tolerance in the cells. Thus, a control manner that first raises the temperature to the highest level and then drops it to the lowest level, comparing with the case of a 15°C constant, seems to be effective to reduce the water loss of the fruit during storage.

These results suggest that a control manner changing flexibly and optimally on the basis of fruit responses is a better way to reduce the quality losses of the fruit during storage than a conventional control manner keeping constant at the lowest temperature.

7. CONCLUSIONS

In this study, the optimal *l*-step set points of the temperature that minimize the rate of the water loss of the fruit during storage were found using a decision system consisting of neural networks and genetic algorithms. The decision system allowed the optimal *l*-step set points of the temperature to be successfully sought through simulation. Several types of optimal values were obtained under different constraints of the temperature and the evaluation length of the control process. Most of them were the combination of the highest and lowest temperatures in the given range. Single and double applications of the highest temperature (40°C), which were called as single heat stress and double heat stress, were effective to reduce the water loss of the fruit. This is because the change in the sudden rise and drop of the temperature has a tendency to decrease the water loss of the fruit. These results suggest that a flexible control of the storage environment on the basis of fruit responses, which is known as a SFA, is more effective to improve the fruit quality during storage than a conventional constant-value low control of the temperature.

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