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Optimization of heat treatment for fruit during storage using neural networks and genetic algorithms

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Abstract

Heat treatment during storage is effective in delaying the ripening of fruit. In this study, an optimal pattern of the heat treatment for tomatoes was investigated based on their surface color, using an intelligent control technique consisting of neural networks and genetic algorithms. An objective function was given by the reciprocal number of the average value of the color change from green to red. For optimization, the control process was divided into l-steps. First, the time-history change in the surface color, as affected by temperature, was identified using neural networks. Then, l-step setpoints of temperature which maximized the objective function were sought through simulation of the identified neural-network model, using genetic algorithms. This technique allowed an optimal heat treatment to be successfully sought when the diversity of the population was kept at a high level in the evolution process. Two types of optimal heat treatments were obtained. One was the single application of heat, which is similar to the conventional type, and the other was intermittent application, given periodically. Finally, the two optimal treatments were applied to an actual system. The result showed that they gave better results on ripening than continuous cooling. Thus, this control technique seems to be suitable for optimization of the storage process for fruits and vegetables. © 1997 Elsevier Science B.V.

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1. Introduction

In recent years, there has been much interest in heat treatment for improving the fruit quality during the storage process (Klein and Lurie, 1990). Some researchers have reported that heat treatment during the storage process seems to be able to inhibit ethylene production, lycopene synthesis, and chlorophyll. All of these factors influence the ripening process of tomatoes (Biggs et al., 1988; Lurie and Klein, 1991, 1992; McDonald and McCollum, 1996). It is also reported that heat treatment can maintain better firmness of apples (Tu and De Baerdemaeker, 1996). The heat treatment can be done in the short term (up to 60 min in water) at 45 to 60°C and long term (12 h–4 days in air) at 38 to 46°C (Lurie and Klein, 1992). Also, Biggs et al. (1988) have demonstrated that heat treatments above 35°C are effective to inhibit chilling injury and ripening. These reports show the possibility to improve the quality of fruit if an optimal heat treatment can be found. In general, however, it is very difficult to find an optimal heat treatment because the mechanism is quite complex and uncertain.

In order to realize the optimization of the storage process, the monitoring of physiological responses of fruit, which are known as 'fruit responses', and its effective uses for control are essential because the physiological status varies with time. This concept is called SFA (speaking fruit approach) (De Baerdemaeker and Hashimoto, 1994; Hashimoto et al., 1995). Nowadays, studies on SFA have become a center of attraction in post-harvest technology. In this study, an optimal heat treatment is determined based on the concept of SFA.

Intelligent approaches such as neural networks and genetic algorithms make the treatment of complex systems easier. Neural networks have the capability of identifying complex nonlinear systems with their own high learning ability (Chen et al., 1990; Hunt et al., 1992). On the other hand, genetic algorithms are effective for finding an optimal value in the complex optimization problem by simulating the biological evolutionary process, based on crossover and mutation in genetics. An optimal value can be searched for in parallel with a multi-point search procedure, not a single point procedure (Goldberg, 1989; Holland, 1992). A SFA-based intelligent control technique consisting of neural networks and genetic algorithms has been developed for the optimization of complex control processes in plant and fruit factories (Morimoto et al., 1995a,b, 1996). In this technique, the neural network is used for the identification of fruit responses, as affected by environmental factors, and the genetic algorithm for the search for an optimal value through simulation of the identified neural-network model.

The aim of this study is to find an optimal heat treatment for delaying the ripening of fruit using a SFA-based intelligent control technique consisting of neural network and genetic algorithms. The control input is temperature and the control output is the change of the color representing the ripening of fruit.

2. Optimization problem

2.1. Fruit materials

The fruit used for the experiment is tomato (*Lycopersicon esculentum* Mill. cv. Momotaro) which is known as a healthy fruit and is suited for fruit production in plant factories. Mature green tomatoes of uniform size (about 8 cm in diameter) and color were stored in a storage chamber (Tabai-espec, LHU-112M), where the temperature and relative humidity are controlled with the accuracy of ± 0.1°C and ± 2%, respectively. Five tomatoes were used for each experiment.

The ripening of tomato was estimated from the surface color. The color change was measured using a colorimeter (Minolta, CR-200b). Here, a hue angle in the L.C.H. method was used for evaluating the color of tomato, which is defined as red = 0°, yellow = 90°, green = 180°, and blue = 270° (Thai et al., 1990; Thai and Shewfelt, 1991). In this case, though the change in the hue angle from green (180°) to red (0°) is usually given as a decreasing response, we treated it as an increasing response by reversing the response and also taking 0° as an initial value, which is called a 'color change', for easier treatment of the color.

2.2. Objective function and optimization problem

Heat treatment for fruit during storage is useful to delay the ripening. However, since the relationship between the heat treatment and the physiological mechanism of fruit is quite complex and uncertain, the optimal pattern has been not obtained yet. It should be systematically determined based on fruit responses such as the color change of fruit.

Let $C_T(k)$ ($k = 1, 2, \ldots, N$) be time series of the color change, as affected by temperature $T(k)$, at the time k, which is characterized by a cumulative response. As a measure of delay in the ripening process of tomato, an objective function, $F(T)$, was given by the reciprocal number of the function $P(T)$, derived from the sum of the last four values, $\{C_T(N\text{-}3), C_T(N\text{-}2), C_T(N\text{-}1), C_T(N)\}$, in the cumulative response of the color change.

$$P(T) = \alpha \cdot \sum_{k=N-3}^{N} C_T(k) + \beta \cdot \sum_{k=N-3}^{N} \{C_T(k) - C_T(k-1)\} \tag{1}$$

$$F(T) = 1/P(T) \tag{2}$$

$P(T)$ consists of two evaluation factors: the amplitude of color change and its change rate. In this study, not only the amplitude of the color change but also the change rate were used for evaluating the ripening process. This is because smaller change rate means more constant value, and the combination of these two evaluation factors is effective to search for an optimal response quickly from among numerous responses, which include many undesirable responses, generated through simulation. The reason of making it a reciprocal number is due to the transformation from minimization to maximization problems to fit the behavior of fitness for evolution in the genetic algorithm application. It is also noted that only the last four values in the cumulative response are used for the objective function because the ripening of fruit is often evaluated based on the value at the last day.

For control, furthermore, the control process was divided into eight steps because the control period was 8 days. The optimization problem in this study is to determine the eight-step setpoints of temperature which maximize the objective function. The constraint of temperature was determined to be $5 \leq T(k) \leq 35°C$ through preliminary experiments on heat treatment (Biggs et al., 1988).

3. SFA-based intelligent control technique

3.1. A method for obtaining an optimal heat treatment

The physiological status of the fruit vary with time. How is fruit responses utilized for determining an optimal heat treatment? Fig. 1 shows the schematic diagram of a SFA-based intelligent control technique combined with neural networks and genetic algorithms, by which an optimal heat treatment is systematically determined based on fruit responses. In this technique, the neural network is first used for identifying and modeling the color change, as affected by temperature, and then the genetic algorithm is used for searching for the eight-step setpoints of temperature (optimal heat treatment) which maximize the objective function through simulation of the identified neural-network model. Furthermore, the

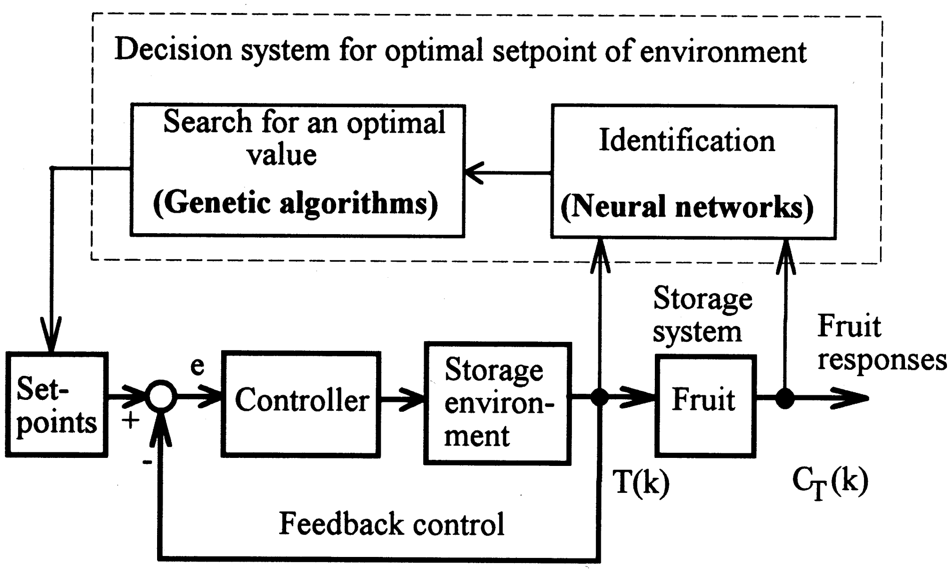

Fig. 1. Block diagram of a SFA-based intelligent control technique consisting of neural networks and genetic algorithms.

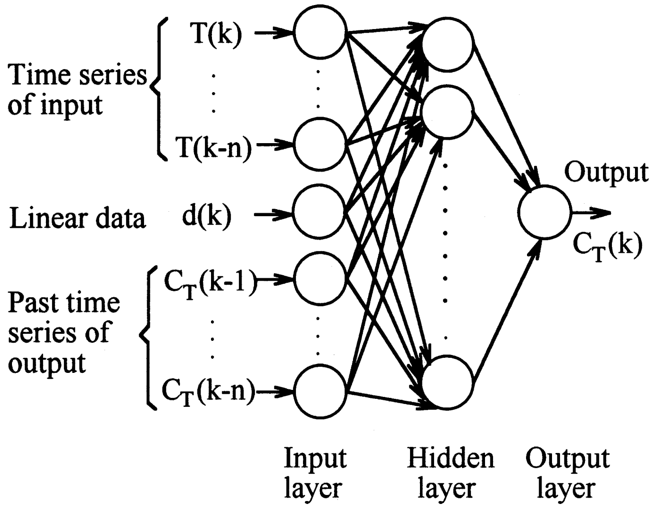

Fig. 2. Schematic diagram of the structure of a three-layer neural network used for identification of cumulative responses such as the color change of fruit.

optimal eight-step setpoints are sequentially applied to the setpoint in the feedback control system. It will be shown that if these two procedures, identification and the search for an optimal value, are periodically repeated in order to adapt the time-variation of the storage system, two types of control performances, optimization and adaptation, can be satisfied.

3.2. Neural network for identifying color change

The ability of identifying complex nonlinear systems is the most important feature of the neural network. Until now, a mathematical model for predicting the effect of time and temperature on the color change of tomato has been employed (Shewfelt et al., 1988). It is a deterministic model based on an exponential equation. Here, the neural network is used for identifying the time-history change in the color change as affected by temperature. Fig. 2 shows the structure of a three-layer neural network used for identification. Cybenko (1989) showed that a three-layer neural network with one hidden layer allowed any continuous function to be successfully identified. From our experiments also, similar results were obtained (Morimoto et al., 1991). It is also noted that the reason we use historical input and output data is to describe the dynamic characteristics of the system. On the other hand, by adding a linear data $\{d(k) = 1, 2, \ldots, N\}$ to the input of the neural network as shown in the figure, the identification accuracy for any cumulative responses was significantly improved (Morimoto et al., 1995b). Therefore, the $(n+1)$th time series of input (temperature) as stated as $\{T(k), T(k\text{-}1), \ldots, T(k\text{-}n)\}$, a linear data $\{d(k)\}$, and nth past time series of the output (color change) as stated as $\{C_T(k\text{-}1), \ldots, C_T(k\text{-}n)$ were applied to the input layer and the current value of the color change,

$C_T(k)$, was used as reference value (k: sampling time, n: number of system parameter). The system parameter number (n) and the neuron number in hidden layer were determined through trial and error. The learning (training) method for neural computation was error back-propagation (Rumelhart et al., 1986; Hint, 1992).

3.3. Genetic algorithm for searching for an optimal value

Genetic algorithms search for an optimal value in parallel with multi-point search procedure by simulating the biological evolutionary process, based on crossover and mutation in genetics (Holland, 1992; Goldberg, 1989; Krishnakumar and Goldberg, 1992). The search space in an actual (complex) problem is usually enormous and the objective function has many peaks. The multi-point search procedure in the genetic algorithm focuses its attention on the most promising parts of the solution space and, consequently, a global, near optimal value can be rapidly and efficiently sought from very large search space. The genetic algorithm needs only the objective function to guide its search. There is no requirement for mathematical equation or any priori knowledge (Holland, 1992). Here, it is used for finding an optimal heat treatment.

3.3.1. Definition and coding of an individual

In order to use the genetic algorithm, we have to define an individual, which means a decision variable to be determined. Since the control process consists of eight-steps, an individual was defined as eight-step setpoints of temperature $\{t_1, t_2,\ldots, t_8\}$ and they were all coded as a 6 bit binary strings as follows:

$$\text{Individual } i = t_{1i}, t_{21}, \ldots \quad t_{1i} = \boxed{100100}\boxed{001001} \quad \ldots \boxed{101010}$$

The constraint of temperature was $5 \leq T(k) \leq 35$°C while temperatures of $0 \leq T(k) \leq 63$°C are obtained from the 6-bit binary string.

3.3.2. Flow chart of a genetic algorithm

Fig. 3 shows the procedure for obtaining an optimal value using a genetic algorithm. Step 1: the initial population consisting of N_{i} (= 6) types of individuals is generated at random. Step 2: N_{o} (= 50) types of individuals are added to the original population from another population which is completely independent on the original one. Step 3: crossover and mutation operators are applied to those individuals. Through the crossover, N_{c} sorts of individuals are newly created according to the crossover rate P_{c} and furthermore N_{m} sorts of individuals are newly generated according to the mutation rate P_{m}. From these operations, N ($= N_{\mathrm{i}} + N_{\mathrm{o}} + N_{\mathrm{c}} + N_{\mathrm{m}}$) types of individual are obtained. Step 4: The fitness of all individuals is calculated using the identified neural-network model. Step 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.

3.3.3. Operations of crossover and mutation

The crossover operation is a single crossover. Two individuals (000011 and 101111) are first mated at random. Next, these binary strings are cut at the 3-bit position along the strings and then two new individuals (000111 and 101011) are generated by swapping all binary characters from the 1-bit to 3-bit position. In this study, two types of crossovers consisting of one step and two steps were implemented. The former is the mating of individuals within the original population and the latter is the combination of both mating of the former type and the mating of individuals in the original and another population. On the other hand, mutation is

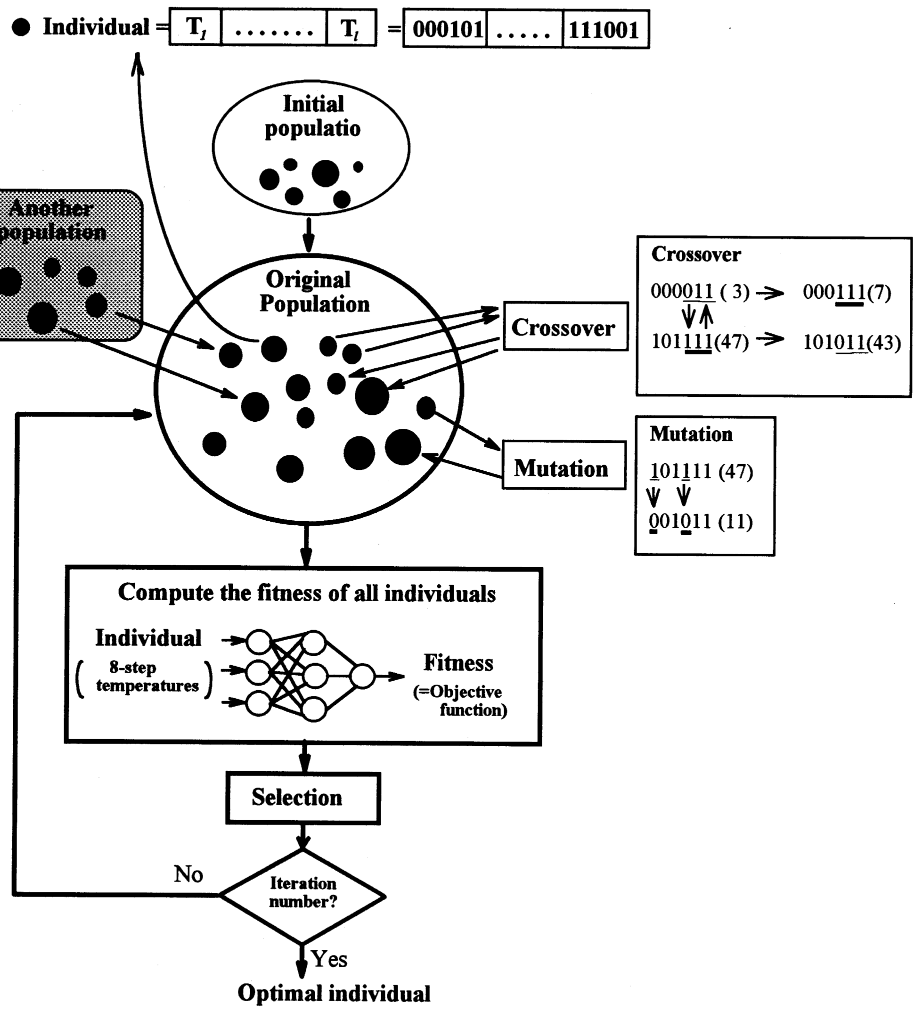

Fig. 3. Flow chart of the genetic algorithm used for searching for an optimal value. The fitness (objective function) of all individuals is calculated using an identified neural-network model.

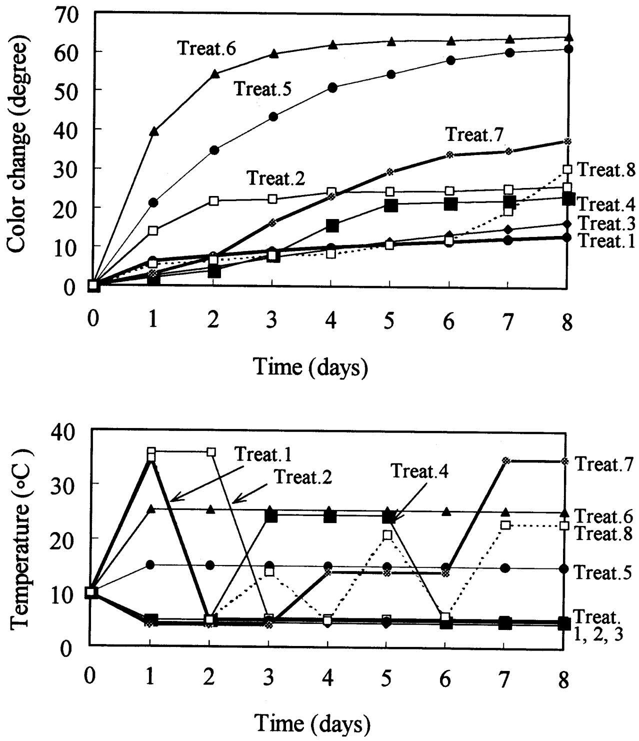

Fig. 4. Observed cumulative responses of the color change of tomatoes as affected by temperature. Larger value of the color change means redder.

a two point operation. One individual (e.g. 101111) is first selected at random, and then a new individual (001011) is created by inverting two characters (genes), selected at random, from 0 to 1 or 1 to 0.

4. Results and discussion

4.1. Actual responses of the color change

The first step is to obtain the actual data for identification. Fig. 4 shows eight types of cumulative responses of the color change of tomatoes under different temperature conditions during storage, in which responses to heat treatment are also included. In all cases, initial temperatures were 10°C. Treatments 1 and 2 are cases of heat treatment in which the tomatoes were heated at 35°C during the first 1 day and 2 days, respectively, and then cooled to 5°C during the latter stages in both cases. Treatments 4, 7 and 8 are the cases of $\{T(k) = 5, 5, 25, 25, 25, 5, 5, 5°C\}$, $\{T(k) = 5, 5, 5, 15, 15, 15, 35, 35°C\}$ and $\{T(k) = 5, 5, 15, 5, 23, 5, 24, 24°C\}$, respectively. Treatments 3, 5 and 6 are cases of constant temperatures 5, 15 and 25°C, respectively. These patterns of temperature were arbitrarily determined so that the time history of the input provides adequate change for better identification.

The amplitude of the color change generally increased with temperature. Comparing color changes in treatments 1 and 3, however, it can be seen that the amplitude under the heat treatment is smaller than that under the continuous cooling treatment during the last 4 days. Therefore, treatment 1 was better than treatments 2 and 3. Thus, it is clear, in the same figure, that treatment 6 provides the greatest deceleration in color change of all the treatments, whereas treatment 3 (like treatment 1) does not require a large deceleration in order to reduce the color change to a low rate. The significance of the comparison is in relation to the justification in the second term in the objective function $P(T)$ in Section 2.2.

4.2. Identification and modeling of the color change

Next, the color responses, as affected by temperature, shown in Fig. 4, were identified using a neural network. Purwanto et al. (1996) investigated how many data sets are necessary in identifying the cumulative response such as a color change under the use of neural networks. They found that three or more data sets are necessary for acceptable identification. In this case, however, six data sets (treatments 1, 2, 3, 5, 6 and 7) were used for identification (modeling) and two data sets (treatments 4 and 8) for evaluation of the model among the eight data sets. This method of evaluation is known as cross validation.

As for the number of system parameter n, the smallest number, $n = 1$, was selected because the data number ($N = 8$) in each cumulative response is small for identification. On the other hand, the hidden neuron number of the neural network was determined through trial and error. Fig. 5 shows the relationship between the hidden neuron number and the estimated error in the identification of the testing data sets. It is found that the estimated errors for three or more neuron number are small, and 4 hidden neurons gave a minimum error. Through these considerations, the numbers of the system parameter and the hidden neurons were determined to be 1 and 4, respectively.

Fig. 6 shows one of the comparisons of the estimated response, calculated from a neural-network model, and the observed response of the color change of tomatoes. A testing data set (treatment 4), which is quite different from the training data sets, was used for this comparison. The system parameter number and the hidden neuron numbers were 1 and 4, respectively. It can be seen that the estimated response shows reasonable agreement with the observed response. This means that we could obtain a computational model for calculating the objective function (fitness), as affected by any combination of eight-step setpoints of temperature.

4.3. Search of an optimal heat treatment using genetic algorithms

Next, the optimal eight-step setpoints of the temperature (optimal heat treatment) were searched for through simulation of the identified model using the

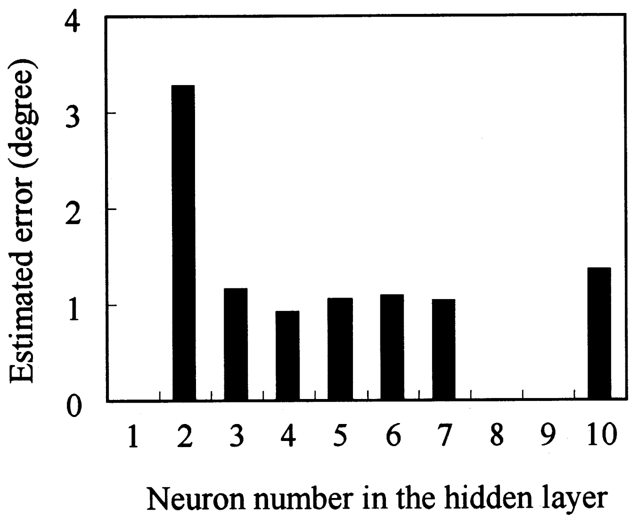

Fig. 5. Relationship between the neuron number in the hidden layer and the estimated error of the color change.

genetic algorithm. Fig. 7 shows evolution curves in searching for an optimal value. The searching performance usually depends on the diversity of the population. Treatment 3 (▲) represents the case when the crossover was carried out based on the individuals within the original population; treatment 2 (○) the case when several (50) individuals in another, completely independent population were added to the original population, and treatment 1 (●) the case when several (50)

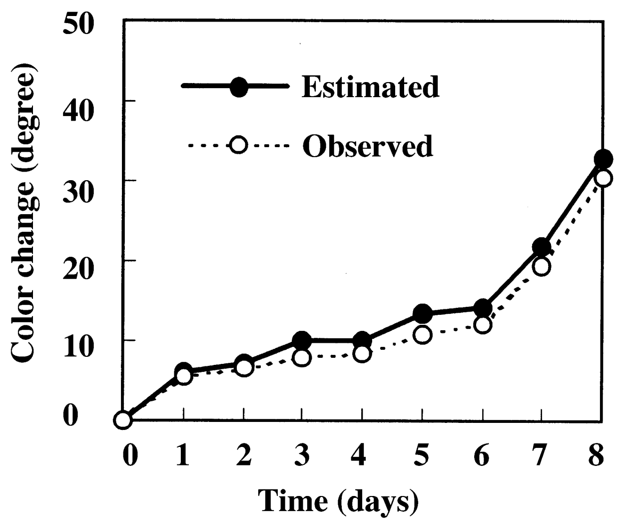

Fig. 6. Comparison of the estimated response and the observed response of the color change of the tomatoes.

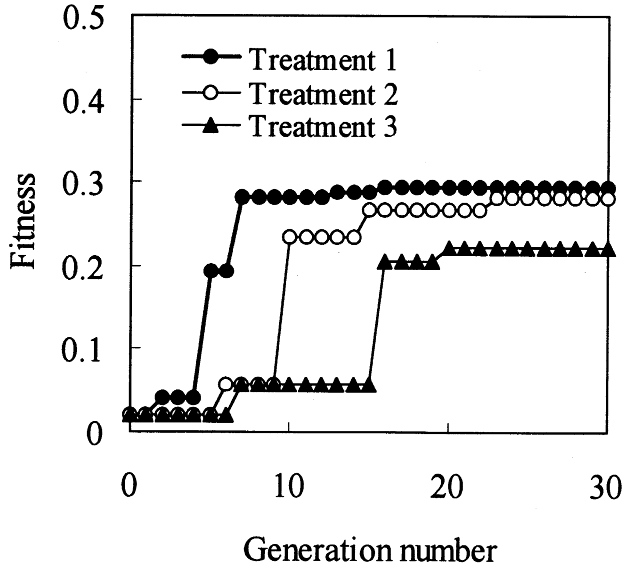

Fig. 7. Evolution curves in searching for an optimal value under different search procedures of the genetic algorithm.

individuals in the other population were added to the original population and, moreover, the crossover took two steps. The mutations in all cases were carried out within the original population. The crossover rate and the mutation rate were 0.8 and 0.6, and the two weights, α and β, in the objective function were 1.0 and 1.0, respectively. The selection technique was based on an elitist strategy which retains an individual with maximum fitness for the next generation in each generation.

From the curve in the treatment 1, the fitness (the value of objective function) dramatically increased with generation number and then reached the maximum value. The searching procedure is usually stopped when the fitness continues to keep the same maximum value with increased generation number, and an optimal value can be given by an individual with this maximum fitness. So, an optimal value was obtained at the 15th generation in the case of treatment 1. In the case of treatment 3, on the other hand, the fitness could not reach a maximum value. This means that the search for an optimal value fell into a local optimum.

The elitist strategy used in this study is known as an effective way for improving the fitness of individuals because an individual with maximum fitness is compulsorily remained for next generation. However, its searching performance can easily fall into a local optimum because only the superior individuals with higher fitness are picked in each generation. In this case, however, a global optimal value could be successfully obtained by increasing the diversity of the original population by adding quite different individuals from another population.

It is noted that there is no guarantee to yield a global optimal solution in the search by genetic algorithms. It is, therefore, important to confirm whether an optimal value determined by the genetic algorithm is global or local. In this paper, the confirmation was carried out using a round-robin algorithm which examines all possible solutions around the near optimal solution (from $T_{opt} - 5$ to $T_{opt} + 5$) obtained by the genetic algorithm at the proper steps of temperature. Through these procedures, a global optimal value could be obtained.

4.4. Optimal heat treatment and the control performances

Fig. 8 shows two types of optimal heat treatments and cooling treatment and the corresponding control performances of the color change, obtained from simulation. The optimal eight-step setpoints of the temperature (optimal heat treatment) depended on the initial condition of the fruit and two weights, α and β, in the objective function. Consequently, two types of optimal heat treatments shown in this figure were obtained through simulation. One is the single application of the heat like a $T(k) = \{35, 5, 5, 5, 5, 5, 5, 5°C\}$ which is the same as a conventional type (...) and the other is an intermittent application like a $T(k) = \{35, 5, 35, 5, 35, 5, 35, 5°C\}$ (——). It can be seen that the color change is smaller in the two optimal heat treatments than in the cold treatment. Comparing responses in the two optimal

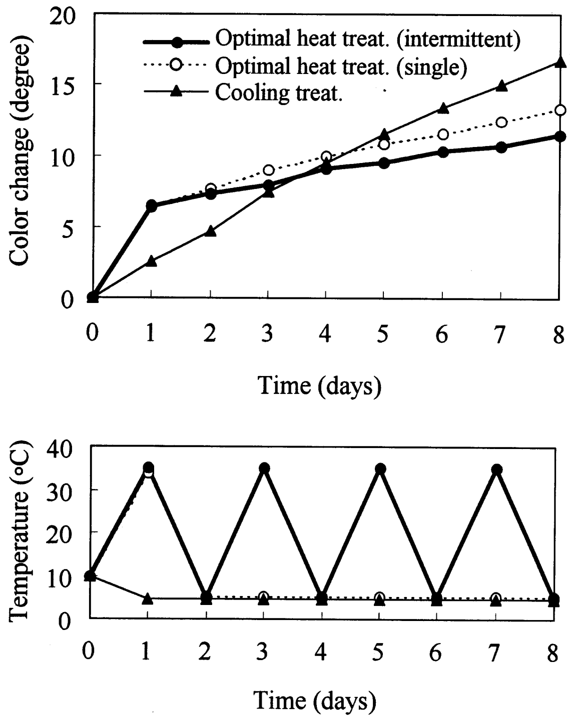

Fig. 8. Two types of optimal heat treatments and cooling treatment and the corresponding control performances of the color change, obtained from simulation.

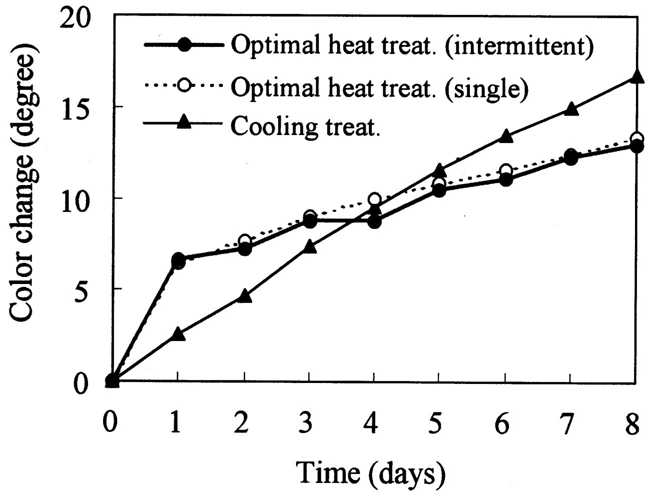

Fig. 9. Actual control performaces of the color change as affected by two types of optimal heat treatments and cooling treatment which are the same as the inputs in Fig. 8.

heat treatments, furthermore, the color change in the intermittent application is slightly smaller than that in the single application. This simulation suggests that several applications of the heat may be more effective than a single application.

Finally, the two types of optimal heat treatment were applied to a real system using the storage chamber explained in Section 2.1. Fig. 9 shows the control performances of the color change. The control inputs are the same as those in Fig. 8. The bold and solid line is the case of the intermittent heat treatment, the dotted line the case of the single heat treatment and the solid line the case of the cold treatment (5°C). It is clear that the color changes under the two optimal heat treatments are smaller than that under the cold treatment. However, there was no significant difference in the color change between the two optimal heat treatments.

5. Conclusions

In this study, the optimal pattern of heat treatment was investigated using a SFA-based intelligent control technique consisting of neural networks and genetic algorithms. A three-layer neural network was effective for identifying the cumulative responses in the color change, as affected by temperature, including heat treatment. The genetic algorithm allowed the optimal setpoints to be successfully searched for through simulation of the identified neural-network model. In this case, by adding several individuals from another population, the searching performance was significantly improved. Two types of optimal heat treatments, a single type (conventional type) and a multiple type, were obtained. Both were effective for delaying the ripening of tomatoes in the actual system. These results suggest that the optimal pattern of the heat treatment may be not constant but changeable with time, place and the physiological status of the fruit. Our control technique allows such time-varying characteristics to be successfully treated by repeating two procedures: identification of fruit responses at the present time and the search for an optimal value through simulation of the identified model. Thus, an intelligent control technique consisting of neural networks and genetic algorithms seems to be suitable for the optimization of such complex systems as fruit-storage systems. For further steps of this study, we plan to apply this technique to optimization of a multi-input (temperature, humidity, etc.) multi-output (color, water loss and firmness) system, aiming at more effective improvement of fruit quality.

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