A Decision and Control System Mimicking a Skilled Grower's Thinking Process for Dynamic Optimization of the Storage Environment

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A decision and control system mimicking a skilled grower's thinking process is proposed which was then applied to dynamic optimization of the relative humidity that minimizes both the water loss and the fungal development of fruits during storage. A skilled grower's thinking process consists mainly of two steps: (1) “learning” through experience and (2) “selection and decision” through simulation of a mental model developed in his brain by the learning. After a decision, (3) “action” in a loose and/or sophisticated manner is taken. The decision and control system proposed here consists of two decision systems (I and II) and a fuzzy on-off controller for ventilation. The optimal set points of the relative humidity are first determined using decision system I, and then the relative humidity is controlled based on these set points using a fuzzy on-off controller. In decision system I, neural networks identify the water loss and fungal development of the fruit as affected by the relative humidity (“learning”), and genetic algorithms search for the optimal set points of the relative humidity that minimize the water loss and fungal development of the fruit through simulation of the identified model (“selection and decision”). The optimal set points obtained here involved a slightly low humidity during the first few days after storage and then higher humidity. The fuzzy on-off controller tuned optimally by decision system II showed good control of the relative humidity. This control technique is widely applicable to dynamic optimizations of complex agricultural systems.

Keywords: decision and control system, thinking process, dynamic optimization, storage environment, intelligent approaches

INTRODUCTION

In recent years, a demand for qualitative improvement of fruit during storage has become important from the viewpoint of food reserves. In order to achieve qualitative improvement of fruit during storage, it is important to flexibly and optimally control the environmental factors based on the physiological responses of the fruit. Such an approach is known as the “speaking fruit approach (SFA)”, where the environmental factors are considered to be the input and the fruit responses the output (De Baerdemaeker and Hashimoto, 1994; Morimoto et al., 1997a and 1997b). The concept of the SFA plays an important role in optimizing...
fruit-storage processes.

In general, however, it is difficult to utilize such fruit responses for the optimization because their physio-ecological behaviors, as affected by environmental factors, are characterized by complexity and uncertainty. Nonlinearity, time-variation and saturation are the major factors for their complexity.

A skilled grower can deal well with many types of crops during cultivation and fruits during storage using his own intuition and experience. In order to realize the optimization of complex systems such as agricultural production processes, therefore, it seems very useful to imitate the thinking procedure for decision and control (Morimoto et al., 1997b and 1999).

It is well known that intelligent approaches such as neural networks, genetic algorithms and fuzzy logics are effective tools for imitating the skilled grower's techniques. Neural networks mimic the biological human learning process and can identify nonlinear relationships between inputs and outputs of a system with their own high learning abilities (Hunt et al., 1992). Genetic algorithms mimic the biological evolutionary process and determine an optimal value in parallel with a multi-point search procedure, based on crossover and mutation in genetics (Goldberg, 1989; Holland, 1992). Fuzzy control techniques seem to be effective for controlling complex ill-defined systems, in which a skilled human operator plays an important role (Lee, 1990a and 1990b). We have developed several types of optimization techniques for cultivation and storage processes using intelligent approaches (Morimoto et al., 1995, 1996, 1997b and 1999).

This paper presents a decision and control system mimicking a skilled grower's thinking process which was then applied to optimization of the relative humidity in a fruit-storage house. With this technique, neural networks, genetic algorithms and fuzzy control are successfully employed for mimicking the "learning", "decision" and "actions" of a skilled grower.

**DESIGN OF A DECISION AND CONTROL SYSTEM**

*A skilled grower's technique.* A skilled grower can deal well with crops based on his own intuition and experience. Considering a skilled grower's thinking process for cultivation, it consists mainly of two steps. The first step is a "learning process". A grower first cultivates a crop by trial and error over several years and then learns the growth behaviors of the crop from experience. This is the process of making his own knowledge model of crop growth in his mind through learning. The second step is a "selection and decision process" of the best cultivation method. A grower simulates the crop growth using the mental model built in his brain and then selects the best strategy for the next cultivation. After a decision, a grower takes an "action" for the best strategy. Finally, a grower operates some controllers to achieve the best strategy in a loose and/or sophisticated (highly skilled) manner. These procedures, (1) learning, (2) decision and (3) action, can be realized by introducing neural networks, genetic algorithms and fuzzy logic. In this study, a decision and control technique mimicking a skilled grower's procedure is proposed to deal successfully with two optimization problems.

*A decision and control system.* Figure 1 shows the decision and control system consisting of two decision systems (I and II) and a fuzzy controller of ventilation. The fuzzy controller controls the storage environment, following its optimal set points as determined by decision system I. The two decision systems (I and II), which are both composed of neural networks and genetic algorithms, respectively determine the optimal set points of the storage environment and the optimal membership functions and control rules in the fuzzy controller. In decision system I, a neural network is used for identifying fruit responses (e.g., water loss
Fig. 1 A decision and control system consisting of a fuzzy controller (on-off controller for ventilation) and two decision systems (I and II) which are both composed of neural networks and genetic algorithms.

and fungi development), as affected by the storage environment (e.g., relative humidity), and a genetic algorithm for searching for the optimal $i$-step set points of the storage environment. In decision system II, on the other hand, a neural network is utilized for identifying the responses of the storage environment (e.g., relative humidity), as affected by on-off of ventilation controlled by the fuzzy controller, and a genetic algorithm for searching for the optimal membership functions and control rules in a fuzzy controller.

It is found that this control technique including neural networks, genetic algorithms and the fuzzy controller well reflects a human thinking process. The first action, measurement and identification, using neural networks, are similar to the manner in which a skilled grower makes a mental model in his brain through learning or experience (learning). In the second step, the way to obtain an optimal value corresponds to the procedure by which a skilled grower selects a better (or best) strategy from his own experience and prediction (decision). Finally, the actions by the fuzzy controller are almost the same as a skilled grower's manual actions (actions).

OPTIMIZATION PROBLEMS

Oranges (*Citrus* “Iyokan”) were used for the experiment. Iyokan fruits are usually picked before the climate turns cold, up to December, to prevent cold injury. At this time, however, Iyokan fruits are not ripe yet. Hence, they are stored in a storage house for 2 or 3 months. The Iyokan fruits mature throughout this storage process, so the environmental control of the storage process is very important.

Since Iyokan fruits have a large evapotranspiration, relative humidity in the storage house becomes high due to their continuous evapotranspiration. An excessively high humidity near 100% RH accelerates the activities of fungi and pathogenic bacteria and then induces many types of spoilage (Kitagawa, 1989). On the other hand, an excessively low humidity induces the wilting of the fruit’s surface. Therefore, it has been determined that an optimal relative
humidity value does exist for this type of storage, while the control is concentrated on efficiently reducing the relative humidity.

In this study, two optimization problems were evaluated. One is to determine the optimal set point of the relative humidity in the storage house, and the other to optimize a fuzzy controller used for maintaining the relative humidity to the optimal relative humidity set point.

**Optimization problem I.** Optimization problem I is to determine the optimal set points of the relative humidity that minimize both the water loss and fungal development of the fruit during storage. The control input is the relative humidity, and the controlled outputs are both the water loss and the fungal development of the fruit. For this experiment, a thermo-hygrostat (Tabai-espec, LHU-112M) was used. The relative humidity was flexibly controlled with an accuracy of 2% RH, and the temperature was maintained at 15±0.1°C.

Let \( W_n(k) \) and \( D_n(k) \) be the time series of the water loss and the fungal development, as affected by the relative humidity \( h(k) \), \( (k=1, \ldots, N: \text{ sampling day}, N: \text{ final day}) \). The objective function \( F_1(h) \) was defined as follows:

\[
F_1(h) = \sum_{k=1}^{N} (\alpha \cdot W_n(k) + \beta \cdot D_n(k)) \tag{1}
\]

where \( \alpha \) and \( \beta \) are the weights for \( W_n(k) \) and \( D_n(k) \). \( W_n(k) \) and \( D_n(k) \) are dynamic responses for the water loss and the fungal development of the fruit as affected by the relative humidity \( h(k) \).

For convenience, the control process was divided into \( l \) steps. Thus, the optimization problem I is to determine the optimal \( l \)-step set points of the relative humidity that minimize the objective function \( F_1 \).

\[
\text{minimize } F_1(h) \\
\text{subject to } 40 \leq h(k) \leq 100\% \text{ RH} \tag{2}
\]

**Optimization problem II.** Optimization problem II is to determine the optimal membership functions and control rules for the fuzzy controller used for maintaining the relative humidity at the optimal set point. The control input is the on-off operations of ventilation \( v(k) \) using a fan, and the controlled output is the relative humidity \( h(k) \) in the storage house. For this experiment, a real storage house, which had a 19.8 m² floor area and 3 m height and equipped with a fan (4 m³/min) for ventilation and a side window, was used. It is known that ventilation is the most simple and effective way for dropping the relative humidity. The amount of lyokan fruits was 4 tons.

An objective function, \( F_2 \), representing the control performance, is the error between the set point and the response of the relative humidity as follows:

\[
F_2(v) = \sum_{k=1}^{N} \left( h(k) - h_{\text{set}} \right)^2 \tag{3}
\]

Where \( h(k) \) is the response of the relative humidity, as affected by the on-off operations of ventilation \( v(k) \), and \( h_{\text{set}} \) is the optimal set point (optimal value).

It is noted that the fuzzy on-off control for ventilation functions, only when the relative humidity is above the set point, and only the duration of on-time is determined through fuzzy reasoning. When the relative humidity dropped below the set point, however, the control process is compulsorily suspended. This is because the relative humidity in the storage house immediately increases up to an equilibrium state by the continuous evapotranspiration of many fruits.

Thus, the optimization problem II is to select optimal membership functions and control rules, which minimize the objective function \( F_2 \). The on-off control, which means the control based on the on-off of the input, seems to be the simplest control technique.
minimize $F_2(v)$  
subject to $v(k) = \{\text{on} (=1) \text{ or } \text{off} (=0)\}$  

TWO DECISION SYSTEMS AND A FUZZY CONTROLLER

Decision systems I. Decision system I determines the optimal $l$-step set points of the relative humidity in the storage house. In this method, responses for both the water loss and the fungal development of the fruit, as affected by the relative humidity, are first identified using neural networks, and then the optimal $l$-step set points of the relative humidity which minimize the objective function $F_1(h)$ are searched for through simulation of the identified neural-network model using genetic algorithms.

Figure 2 (a) shows a 3-layer neural network (neural network I) with external dynamics to identify the dynamic responses of the water loss $W_h(k)$ and the fungal development $D_h(k)$. It is noted that the dynamics can be expressed by applying time delay operators to the input and output signals (Chen et al., 1990; Isermann et al., 1997).

Fruit responses such as $W_h(k)$ and $D_h(k)$ are characterized by cumulative responses, which always increase (or decrease). For identification of such cumulative responses, linear data $d(k) = \{k\}$ $(k=1, 2, \ldots, N)$ were also used as the input (Morimoto, 1997c). Hence, the current outputs, $W_h(k)$ and $D_h(k)$, are estimated from the $(n+1)$th historical input data $\{h(k), \ldots, h(k-n)\}$, linear data $d(k) = \{k\}$ and the two $n$th past historical output data $\{W_h(k-1), \ldots, W_h(k-n)\}$ and $\{D_h(k-1), \ldots, D_h(k-n)\}$ ($n$ : system parameter number). The learning method is error back-propagation (Rumelhart, 1986).

The data sampled were divided into two data sets: a training data set for training the neural network and a test data set for evaluating the model accuracy. The system parameter number $n$ and the hidden neuron number of the neural network $n_h$ were determined through cross-validation.

The first step for the GA application is to define an “individual”. Each individual represents a candidate for an optimal solution. Here, because an optimal value is given by
l-step set points of relative humidity \((h_1, ..., h_l)\), each parameter in an individual is expressed with 7-bit binary strings as follows:

\[
\text{Individual} = h(1), ..., h(l) = 0000101, ..., 1110001
\]

Genetic operators, crossover and mutation, are applied to these binary strings. Here, a one-point crossover and a two-point mutation were performed.

Fitness is also defined as an indicator for measuring the individual’s quality for survival. Its concept is similar to that of an objective function in conventional optimization problems. Relatively good individuals with higher fitness reproduce, and relatively bad individuals with lower fitness die during evolution. An individual with maximum fitness means an optimal solution (Holland, 1992).

The evolution speed is significantly affected by the degree of diversity of the population. A lower diversity prevents the evolution of the population. In this study, therefore, 100 individuals in another population were added to the original population in order to maintain the diversity of the population.

Figure 2 (b) shows the flow chart of the genetic algorithm (Morimoto and Hashimoto, 2000). Step 1: The initial population consisting of \(N_i = 6\) types of individuals is generated at random. Step 2: \(N_o = 100\) types of individuals are added to the original population from another population. Step 3: Genetic operations, crossover and mutation, are applied to those individuals. Through the crossover, \(N_c\) sorts of individuals are newly created according to the crossover rate \(P_c(=0.8)\), and \(N_m\) sorts of individuals are then newly generated according to the mutation rate \(P_m(=0.6)\). From these operations, \(N (=N_i+N_o+N_c+N_m)\) types of individuals are obtained. Step 4: The fitness (values of the objective function) of all individuals is calculated using the identified neural-network model. Step 5: \(N_i (=300)\) individuals with higher fitness are selected and retained for the next generation. An optimal value can be obtained by repeating these procedures.

**Fuzzy on-off ventilation controller.** The fuzzy on-off ventilation controller is the main controller and performs sophisticated control of the storage environment according to the optimal set points determined by decision system I.

The fuzzy reasoning was conducted based on Mamdani’s minimum operation rule. A center of area method, which calculates the center of gravity of the possibility distribution of a control action, was used for defuzzification (Lee, 1990b).

Figure 3 (a) and (b) show the membership functions to be tuned and a matrix representing the control rules, respectively. All of the membership functions have very simple and common shapes. In this fuzzy reasoning, the operational time \((=\text{on-time})\) of the ventilation \((T)\) is estimated from the error \((E)\) between the desired value and the real response to the relative humidity and its change rate \((\Delta E)\), on the basis of a fuzzy reasoning (Mamdani’s minimum operation rule). \(E: \{ A_1 = \text{low (L)}, A_2 = \text{medium (M)} \text{ and } A_3 = \text{high (H)} \}; \Delta E: \{ B_1 = \text{negative high (NH)}; B_2 = \text{zero (ZERO)} \text{ and } B_3 = \text{positive high (PH)} \}; T: \{ C_1 = \text{zero (ZERO)}; C_2 = \text{short (S)}; C_3 = \text{medium (M)}; C_4 = \text{slightly long (SL)} \text{ and } C_5 = \text{long (L)} \}\). A center of area method which calculates the center of gravity of the possibility distribution of a control action was used for defuzzification (Lee, 1990b). Parameters on the x-axis \((a, b \text{ and } c)\) are respectively basic values for shaping the three types of membership functions. We assumed that the membership functions on \(E, \Delta E\) and \(T\) are respectively shaped by the multiples of the corresponding basic values \(a, b \text{ and } c\).

As shown in the matrix in Fig. 3 (b), only three output fuzzy sets, \(X_1, X_2 \text{ and } X_3\), in the row, \(A_2\), are objects for tuning. Therefore, both the three basic parameters \((a, b \text{ and } c)\) in the membership functions and three fuzzy sets \((X_1, X_2 \text{ and } X_3)\) are determined so that the objective function \(F_2(v)\) becomes minimum. Hence, the decision variable is given by six parameters \((a, b, c)\).
Thus, optimization problem II is to determine the optimal fuzzy parameters of \((a, b, c, X_1, X_2, X_3)\) which minimize \(F_2(h)\). \(F_2(h)\) is also used for the fitness in the genetic algorithm application.

**Decision systems II.** Decision system II periodically optimizes the membership functions and fuzzy control rules in the fuzzy controller using neural networks and genetic algorithms. This method is the same as that of decision system I.

Karr and Gentry (1993) developed an adaptive fuzzy controller which alters membership functions optimally using genetic algorithms. They searched for optimal membership functions through simulations of a mathematical model using genetic algorithms. Kim et al. (1995) also applied genetic algorithms for the optimization of fuzzy controller for physical systems and demonstrated the robustness of a GA-based methodology. However, it seems to be difficult to apply these techniques to the control of ill-defined complex and unknown systems because the control objects that they treated are well understood and the model is given by a deterministic model.

On the other hand, the technique proposed here uses a neural network identified in real time for modeling of complex systems and searches for the optimal membership functions and control rules using genetic algorithms.

A three-layered neural network was used to identify the dynamic responses of the relative humidity \(h(k)\), as affected by the on-off operation of ventilation \(v(k)\). Here, a single input and single output system was assumed. The identification method is the same as Fig. 2 (a). The current outputs, \(h(k)\), are estimated from the \((n+1)th\) historical input data \(\{v(k), ..., v(k-n)\}\) and the \(n\)th past historical output data \(\{h(k-1), ..., h(k-n)\}\).

In optimization II, the decision variable is given by three basic parameters \((a, b\) and \(c)\) in three membership functions and three parameters \((X_1, X_2\) and \(X_3)\) in the control rules; therefore, an individual is defined as:

\[
\text{Individual} = a, b, c, X_1, X_2, X_3 = 111000, 101010, 001101, 101, 001, 010
\]

The basic parameters, \(a, b\) and \(c\), are coded as 6-bit binary strings and the fuzzy sets \((X_1, X_2\) and \(X_3)\) to be selected from among integer values \((1 : C_1, 2 : C_2, 3 : C_3, 4 : C_4\) and \(5 : C_5)\).
are coded as 3-bit binary strings. Through this coding, we can obtain parameters with the ranges of $0.1 \leq a \leq 6.0$ (% RH), $0.1 \leq b \leq 3.0$ (% RH), $0.1 \leq c \leq 6.0$ (min) and $0 \leq X_1, X_2, X_3 \leq 5$. The search spaces for $a$, $b$ and $c$ were restricted in this manner. This is because the optimal values of $a$, $b$ and $c$ are thought to exist in these ranges based on a rule of thumb. The procedure for the genetic operation is the same as the explanation of Fig. 2 (b).

RESULTS AND DISCUSSION

Dynamic optimization of the relative humidity by decision system 1

Fruit responses as affected by relative humidity. First, real fruit responses as affected by relative humidity were measured to identify their dynamics. Figure 4 shows observed daily changes in the water loss $W_a(t)$ and the fungal development $D_b(t)$ of the fruit under different humidity conditions. Here, four types of data sets were obtained. Responses for the water loss can be seen as almost linear with time. Usually, the water loss of the fruit occurs in proportion to a water vapor pressure gradient between the stored air and the fruit tissue. However, because the water vapor pressure of the tissue depends on the water content of the fruit tissue which gradually decreases with time, the relationship between the water loss and the water content of the fruit shows nonlinear characteristics (Lents and Rooke, 1964; Ng et al., 1995). On the other hand, the fungal development was determined from its infected area. Some fungi were compulsorily inoculated to the blemish part of the fruit in order to get the initial condition of the fungal development. The daily change in the fungal development can be seen as a sigmoid function. Until now, many researchers reported almost the same

![Graph](image)

**Fig. 4** Observed daily changes in the water loss and the fungal development of the fruit under different humidity conditions (training data set).

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responses (Koga and Kobayashi, 1982; Steitz et al., 1982). From both responses, it seems that the water loss and the fungal development can be successfully controlled by the relative humidity.

Identification of fruit responses as affected by relative humidity. Next, real responses in Fig. 4 were used as the training data set to identify the fruit responses using a three-layered neural network shown in Fig. 2 (a). Here, we have four types of training data sets. Purwanto et al. (1996) investigated how many data sets are necessary as the training data set in identifying the fruit response under the use of neural networks. They found that 3 or more training data sets are necessary for acceptable identification. It has been confirmed that the use of four types of training data sets is acceptable for identification. The number of system parameters $n$ and the hidden neuron number in the neural network $n_h$ were determined through cross-validation as follows: $n=2$ and $n_h=20$. These values gave the minimum identification error between the observed and estimated responses. Figure 5 shows the comparison between the estimated response, obtained from the neural network model, and the observed response of $W_h(t)$. Here, a test data set, which was independent of the training data sets, was used to validate the model accuracy. It can be seen that the estimated responses are closely related to the observed ones. This means that a successful computational model (neural-network model) could be obtained for estimating the $W_h(t)$ and the $D_h(t)$, as affected by any profile of the relative humidity.

Dynamic optimization of the relative humidity. Next, the optimal 1-step set points of the relative humidity which minimize the objective function $F_1$ were determined through simulation of the identified neural-network model, using genetic algorithms. Here, we assumed three types of control processes, $l=1$, 2- and 3-step control processes. Figure 6 shows the optimal 1-step set points of the relative humidity determined here and the corresponding control performances of the water loss $W_h(k)$ and the fungal development $D_h(k)$. It is noted that these are all simulation results. The 1-step control process is the same as a constant-value control which keeps the environmental conditions constant during the entire control process. The optimal values determined here were 85% RH for the 1-step, 78%–95% RH for the 2-step and 72%–90%–95% RH for the 3-step processes, which depends on two weights, $\alpha$ and $\beta$, for
Fig. 6 Optimal 1-step ($l=1$, 2 and 3) set points of the relative humidity determined here and the corresponding control performances of the water loss and the fungal development of fruits obtained from simulation.

Based on the figure, the optimal set points have a slightly low humidity during the first few days after storage and then higher humidity. The water loss $W_h(t)$ is smaller in the optimal control than in the constant-value control, though there is no significant difference in the $D_h(t)$. A slightly low humidity in the first step might be effective in preventing fungal development in the storage process. Thus, it seems that, during storage, the flexible control of the environment is more useful than constant-value control for realizing the qualitative improvement of fruit.

The optimal set points of the relative humidity were determined to be 85% RH for the 1-step, 78 → 95% RH for the 2-step and 72 → 90 → 95% RH for the 3-step processes. It is noted that 85% RH is one solution for the 1-step control process. The $W_h(t)$ under the 1-step process can be seen as the largest in the three control processes, while there are no significant differences in the $D_h(t)$ in the three control processes. No differences in both $W_h(t)$ and $D_h(k)$ were observed between the 2- and 3-step control processes. It is found that optimal set points in the 2- and 3-step control processes have the same tendency, a slightly low humidity during the first few days after storage and then a higher humidity. It can be seen that the combination of a slightly low humidity during the first few days after storage and a higher humidity during the latter half of the control process.

Figure 7 shows the evaluation of the control performances in the three control processes,
where the values of the fitness are compared. It is found that the values of fitness are smaller in the 2- and 3-step control processes than in the 1-step control process. Thus, dividing the control process into several steps provided better control performance.

Optimal control performance of the relative humidity

The next step is to pursue the optimal relative humidity profile (l-step set points), determined by decision system I, efficiently (or optimally) using the fuzzy on-off controller for ventilation. This was achieved through optimization of the fuzzy controller, in detail by selecting optimal membership functions and control rules. Here, the control input is the on-off operation of the ventilation, and the control output is the relative humidity in the storage house.

Measurement and identification of the relative humidity as affected by ventilation. The dynamic response of the relative humidity, as affected by ventilation, was first identified based on the real data using the neural network in decision system II. It is noted that an acceptable model can be obtained by this procedure (identification method) even if the quantity of the orange changes, because the identified model is tuned in proportion to the quantity of the orange, and the optimum fuzzy parameters are adjusted by it. Figure 8 shows the identification result, where the observed response (test data set) and the estimated response were
compared to evaluate the model accuracy. The estimated response is closely related to the observed response. We selected $n=15$ as the best system parameter number, through cross-validation, because it gave the minimum identification error.

Optimization of the fuzzy controller and the optimal control of the relative humidity. Next, the optimal parameters ($a$, $b$, $c$) in the membership functions of the fuzzy controller shown in Fig. 3 were determined to be 2.0, 0.5 and 1.3, respectively. The optimal fuzzy sets ($X_1$, $X_2$, $X_3$) were also estimated to be "zero" ($=1$), "short" ($=2$), and "middle" ($=3$), respectively, through simulation of the identified neural-network model using the genetic algorithm in decision system II.

Figure 9 shows a comparison of the control performances of the relative humidity in the storage house between the optimal fuzzy on-off ventilation control and a simple on-off ventilation control which means a conventional on-off feedback control with relay operation. The control aim is to pursue the optimal 2-step set points of the relative humidity (78 and 95% RH). It is found that the performance of the fuzzy on-off control is superior to that of a simple on-off control.

Thus, in the on-off control of the relative humidity in the storage house by ventilation, the control accuracy was significantly improved by using the optimized fuzzy on-off controller.

**CONCLUSIONS**

For optimization of storage processes, a new intelligent control technique mimicking a skilled grower’s thinking process was proposed. It consists of a fuzzy on-off controller and two decision systems and was applied it to the dynamic optimization of the relative humidity in the storage house. The two decision systems I and II, both of which consist of neural networks and genetic algorithms, respectively determine the $l$-step optimal set points of the relative humidity based on fruit responses and tunes the fuzzy controller optimally. The optimal pattern of the relative humidity was a slightly low humidity during the first few days after storage and then a higher humidity near 95% RH. This result suggests that the dynamic optimization of storage environment is very useful to improve the quality of fruits during storage. Furthermore, the fuzzy on-off controller optimized showed good control of the...
relative humidity in the storage house. The decision and control technique proposed here is useful for dynamic optimization control of agricultural systems, characterized by complexity and uncertainty, in elaborate and sophisticated manners.

REFERENCES


貯蔵環境の動的最適化のための築農技術を模倣した知能的制御システム

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本研究は、築農家の思考過程と技術を模倣した知能的制御システムを提案し、それを貯蔵における果実の水損失とカビの発生度合いを最小にする相対湿度の最適最適化に適用した。築農家の思考過程は主に2つのステップから成る。1つは経験を通じて“学習する”こと、2つ目は学習で得られた精神的モデル（ニューラルネットワークモデル）を用いてシミュレーションし、すなわちいろいろな操作に対する結果を予測し、その中から適切な操作を“選択・決定する”ことである。さらに、適切な操作を自分の熟練技術に基づいて大胆かつ巧妙に“実施する”。本知能的制御システムは2つの最適値決定システム（IとII）とファジー制御による換気扇のオンオフ制御器から成る。最初に、最適値決定システムIを用いて最適な相対湿度の目標値列が決定され、次にそれに基づいて換気扇のファジー・オンオフ制御により相対湿度が制御される。最適値決定システムIでは、まずニューラルネットワークを用いて相対湿度に対する果実の水損失とカビの発生度合いの応答を同定し（“学習する”）、次に同定されたモデルのシミュレーションから、遺伝的アルゴリズムを用いて、果実の水損失とカビの発生度合いを最小にする相対湿度の目標値列を見出す（“選択・決定する”）。求められた最適目標値列は、貯蔵の初期はやや低湿度にし、後半は高湿度にするパターンであった。最適値決定システムIIで最適化されたファジー・オンオフ制御器は従来のオンオフ制御より優れた制御パフォーマンスを示した。以上のように、本制御システムは農業における複雑な制御システムの動的最適化に広く適用可能と考えられる。