Simulation-based control of enclosed ecosystems - A case study: Determination of greenhouse heating setpoints

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Lacroix, R. and Kok, R. 1999. **Simulation-based control of enclosed ecosystems - A case study: Determination of greenhouse heating setpoints.** Can. Agric. Eng. **41**:175-183. The overall objective of this study was to investigate the use of a simulation-based approach for the control of enclosed ecosystems. To do this, a simulation-based controller was developed and implemented in a simulated greenhouse system. The role of the controller was to determine the setpoint path that would minimize the energy requirements for heating. It did this once a day, for the ensuing 24 hours, by simulating the greenhouse behavior in response to anticipated meteorological conditions. For each day a number of simulations were run for various setpoint scenarios and the most favorable scenario chosen. The greenhouse model that was used for these simulations was a neural network. The strategy used by the controller was based on the supposition that crops have a temperature integration capacity. Overall, the simulation-based controller allowed the greenhouse system to adapt itself to the anticipated disturbances and to behave more optimally than with a reference controller. It maintained high night temperatures when outside temperature and solar radiation intensity were anticipated to be low during the next day and vice-versa. This control approach reduced the average heating load by more than 7%. The results illustrate the adaptive capacity of a simulation-based controller and provides a basis for the use of this approach in various other types of enclosed ecosystems. **Keywords**: Greenhouse control, simulation, artificial neural network.

Afin d'explorer l'utilisation du contrôle par simulation pour des écosystèmes clos, un système de contrôle basé sur la simulation (SCBS) a été développé et implanté dans une serre simulée. Le rôle du SCBS était de déterminer une trajectoire de points de consigne pour le chauffage qui minimiseraient les besoins en chauffage. Cette trajectoire était déterminée une fois par jour, pour les 24 heures suivantes, en simulant avec un réseau neuronal le comportement de la serre en réponse aux conditions météorologiques anticipées et à diverses trajectoires possibles. La stratégie du SCBS était basée sur la supposition que les plantes ont une capacité "d'intégration de la température". Le SCBS a permis à la serre de s'adapter aux perturbations anticipées et de se comporter de façon plus optimale qu'avec un système de contrôle de référence. De hautes températures nocturnes ont été maintenues lorsqu'il était prévu que la température extérieure et les radiations solaires seraient basses durant le jour suivant; des températures basses étaient maintenues dans le cas contraire. L'approche utilisée par le SCBS a permis de réduire de plus de 7%, en moyenne, la charge de chauffage. Les résultats ont mis en relief la capacité d'adaptation d'un SCBS, et ont permis de jeter les bases d'un cadre méthodologique pour la conception de tels systèmes de contrôle, et pour leur implantation dans des écosystèmes clos.

INTRODUCTION

During the last several decades, interest in enclosed ecosystems has grown considerably. For example, all over the world controlled environment agriculture has been expanding with the construction of greenhouses, plant factories, and phytotrons. To maintain the stability of an enclosed ecosystem requires the installation of control equipment to artificially supply many of the abiotic factors like light, nutrients, and heat. Also, many functions that would be carried out by a wide variety of species in natural environments need to be accomplished by mechanical, chemical, or other such means. Pollination, waste treatment, and maintenance of population levels are examples. Consequently, a sophisticated control approach is necessary to manage an enclosed ecosystem.

Until now, humans have usually served as the controllers of enclosed ecosystems because of their cognitive abilities, such as the capacity to experiment, analyse, and learn. To increase the autonomy of enclosed ecosystems, human control needs to be replaced with artificial mechanisms that must also be able to perform some cognitive functions. Mechanisms of that type achieve together what has been called "cognitive control" (Kok and Lacroix 1993). One important aspect of this is "conscious control", defined as control performed by an entity which is "self-aware", i.e., able to refer to models of itself (Clark and Kok 1998; Clark et al. 1999; Lacroix 1994). These models can be used by the entity for diverse purposes like, for instance, to simulate its own behavior in response to disturbances. Accordingly, one interesting aspect of conscious control is that it can allow a system to test many possible strategies in response to anticipated disturbances before implementing a specific strategy that it deems to be the most appropriate for the circumstances.

Thus, one way to confer a rudimentary form of consciousness on an enclosed ecosystem is to give its controller the capacity to simulate on the basis of one or more models of the ecosystem. This type of controller will then perform what can be referred to as "simulation-based control". In this research, that approach was applied to a greenhouse-type enclosed ecosystem. The prototype simulation-based controller (SBC) that was developed had the responsibility of determinining the most appropriate heating setpoints in response to meteorological forecasts. The model used by the controller was an artificial neural network (ANN). ANN's are able to mimic the behaviour of physical systems to a reasonable degree, and they allow for the execution of many simulations in a relatively short time (Shukla et al. 1996). They have been used successfully for greenhouse modelling by Kok et al. (1994) and Seginer et al. (1994). The SBC was implemented in a simulated greenhouse system so that its performance could easily be compared with that of another controller, the "reference controller" (RC).

Throughout this project, apart from studying specifically the impact of simulation-based control on the greenhouse, the aim was also to learn generally about design considerations for this approach and about the kind of behaviour that can be expected from a system that is controlled in this way. Thus, this work has served as the basis for the creation of a conceptual framework for the conscious control of a wide variety of types of ecosystems.

OBJECTIVES

The overall objective of this project was to investigate the use of a simulation-based approach as a rudimentary form of conscious control. The specific objectives were:

1. to create a prototype SBC (using ANN's) whose role was to determine greenhouse heating setpoints that would minimize energy consumption;
2. to investigate, by means of simulation, the controller's effects on heating setpoints, air temperature, and energy requirements of a greenhouse;
3. to initiate the development of a wider framework for the design of simulation-based and conscious control.

THE SIMULATION-BASED CONTROLLER

Control strategy

It has been shown that, within certain limits, many crops respond more to the average temperature over a certain period than to the specific temperature history during that period. For example, the yields of cucumber, tomato, and chrysanthemum were reported to not be significantly affected by various temperature regimes (Cockshull 1988; de Koning 1988a; Krug and Liebig 1980; Langhans et al. 1981). The limits to this "temperature integrator effect" depend on the buffering capacity of the plant, as well as on the amplitude of the temperature fluctuations. It appears that for tomatoes, the crop modeled in this study, the temperature integration period can be greater than 24 hours when temperatures fluctuate between 14°C and 26°C (de Koning 1988c) and as long as one week when temperature fluctuations are smaller (de Koning 1990).

Many authors have suggested that the temperature integration effect can be exploited to reduce heating requirements in greenhouses, etc. without adversely affecting production (Bailey and Chalabi 1991; de Koning 1988c; Hooper and Davis 1988; Miller et al. 1985; O'Flaherty 1989). Specifically, in this regard, the heating setpoint can be lowered when the heat loss factor for a greenhouse is high and increased when the loss factor is relatively low. In this way the temperature integral can be maintained at its desired level while the heating is shifted to periods of lower cost. For example, the setpoint can be reduced when the wind speed is high and then increased when it is low again (Aikman and Picken 1989; Bailey and Seginer 1988; Cockshull 1985; Hurd and Graves 1984). A similar approach for greenhouses equipped with a thermal screen consists of maintaining a higher setpoint during the night when the screen is in place (Bailey 1988; Krug and Liebig 1980) and a lower setpoint when it is not. In this case the energy saved evidently depends on the setpoints used, as well as on the nature of the thermal screen. Assuming a 50% reduction in heat loss factor due to the thermal screen, Bailey and Seginer (1988) calculated that a potential energy saving of up to 15% was possible.

In the research presented here, a simulation-based approach was used that allowed the temperature controller to choose in advance (for the next 24 hours) the heating setpoint trajectory that would minimize the energy consumption of a greenhouse equipped with a thermal screen. In making its decision the controller took into consideration how the greenhouse system would react to the meteorological conditions anticipated for the next 24 hours. For each anticipation period, one daytime and one nighttime heating setpoint were used so as to maintain the temperature integral at a given value.

Functioning of the simulation-based controller

The SBC performed the following tasks: it 1) generated a series of setpoint trajectories that were all expected to lead to the required 24-hour temperature integral, 2) ran simulations to estimate the energy requirements for each trajectory, and 3) chose the trajectory for which the energy requirement was minimum. This was done once per day, at the end of the hour during which sunset occurred. The 24-hour temperature integral to be achieved from one sunset to the next was the same as that produced by the RC, whose functioning is explained further below.

The SBC used the following algorithm. A pair of night and day heating setpoints were generated for testing. To do this, a value was first chosen for the night, and then the corresponding setpoint for the day was calculated so as to maintain the 24-hour temperature integral equal to the target value. This was then repeated for a total of ten pairs of setpoints whose night values ranged from 15°C to 24°C, in 1°C increments. The setpoint values were thus influenced by the lengths of the nights and the days, as calculated from sunrise to sunset. A 24-hour setpoint trajectory was then generated for each setpoint pair and, for each trajectory, a series of simulations was executed by the controller to predict the corresponding greenhouse temperature and heating load histories. These simulations were done with an ANN, whose forcing functions were the meteorological conditions that were anticipated for the next 24 hours. As described further below, perfect weather prediction was assumed for this study.

The series of simulations to be performed for each setpoint trajectory was carried out as follows. Given the trajectory in question, a first simulation was run by the controller. When this was finished, the resulting 24-hour temperature integral (as predicted with the ANN) was compared to the target integral to determine if it was sufficiently close. This was necessary because the predicted greenhouse temperature could, for instance, have been higher than the setpoint due to overheating when the solar radiation intensity and the outside temperature were relatively high. If the difference between the average

Table I. Inputs and outputs of the artificial neural network used by the simulation-based controller.

INPUTS
Day of the year (d)
Current time of the day (h)
Current solar radiation (W/m^2)
Previous value of solar radiation (W/m^2)
Current outside air temperature (°C)
Previous outside air temperature (°C)
Current wind speed (m/s)
Previous greenhouse air temperature (°C)
Current heating setpoint (°C)
OUTPUT
Current greenhouse air temperature (°C)
Current heating requirements (W/m^2)

predicted temperature and the average target temperature was less than 0.2°C, the results were used as they were and the next setpoint trajectory was considered. If, however, the difference was larger than 0.2°C, that whole setpoint trajectory was adjusted accordingly and a new simulation was run. For example, if the difference was 1.5°C, the entire setpoint trajectory was adjusted accordingly by 1.5°C. During this adjustment, the setpoints were, nevertheless, forced to remain below the desired maximum (24°C), as well as above the desired minimum (15°C). Adjustment of the setpoints and re-running of the simulation was repeated a maximum of 30 times. If a significant difference still existed after that, the simulation results were accepted as they were. Once the setpoints were stable for a given trajectory, the energy requirement was determined. Thus, at the end of each day, the entire adjustment/simulation cycle was always carried out for ten different setpoint trajectories and a maximum of 300 simulations could be run at that time. Ten energy requirements always resulted, corresponding to the ten setpoint trajectories, and the one with the lowest anticipated energy requirement was then selected.

The ANN used by the SBC had been previously trained to predict hourly greenhouse air temperature and heating requirement based on the current values of several meteorological variables and the heating setpoint, as well as previous values (i.e., one hour before) of several of these. Inputs and outputs of the ANN are listed in Table I. Previous values were included as inputs to allow the development of a dynamic neural model. Thus, the predicted greenhouse air temperature and heating requirement at a given time were dependent on what had happened during the previous hour which, in turn, depended on what had happened during the hour before that, etc. The day of the year and the time of day were

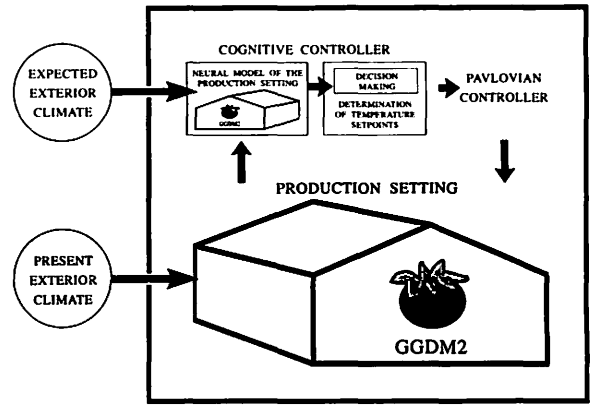

Fig. 1. The general structure of the simulated greenhouse system.

used as inputs to furnish information about the sun's position, as well as about the times of sunrise and sunset, in an attempt to ease the requirement that the ANN implicitly encode the optical properties of the greenhouse cover and the opening and closing times of the thermal screen. Since explicit information about ventilation was not furnished to the ANN, the functioning of the ventilation was also implicitly encoded in the ANN, i.e., it was learned through the data. The architecture and training of the ANN are described in some detail later.

THE DEVELOPMENT PROCEDURE

The experimental greenhouse system

The SBC was installed in a simulated greenhouse system to compare its performance with that of the RC. This greenhouse system was composed of a number of modules which contained models of the greenhouse and of the crop, a weather generator, a Pavlovian controller, a cognitive controller, as well as the simulation manager. As described by Lacroix et al. (1996), the simulation structure was made modular to facilitate studies with other types of ecosystems (e.g., Molenaar 1998). The greenhouse system is illustrated in Fig. 1. The greenhouse model was GGDM2 (Gembloux Greenhouse Dynamic Model), which was developed and validated by de Halleux (1989). In this project it was used to represent a greenhouse equipped with an aluminized thermal screen. Ventilation was carried out with a small fan and a large, two-speed fan (Lacroix 1994). The small fan was switched on when the greenhouse temperature was more than 1.0 °C above the ventilation setpoint and the large fan was switched on at its lower and higher speeds, respectively, when the temperature exceeded the setpoint by 2.0 and 4.0°C, respectively. The ventilation setpoint for the GGDM2 model was kept fixed at 25°C. The Pavlovian controller regulated the greenhouse temperature according to the heating setpoints given to it by the cognitive module. Here, the Pavlovian module consisted of an ON/OFF regulator that was triggered at each simulation step (i.e., every 15 seconds). Either the RC, the SBC, or other heating setpoint generators could be installed in the cognitive module. The same climatological database was used for the simulations of the SBC and of the simulated greenhouse system, so that in the simulations carried out with the ANN for the setpoint trajectory calculations there was exact anticipation of the exterior climate. This represents an ideal situation in which the weather forecasts are perfect.

The reference controller

The effectiveness of the SBC was judged by comparing its performance with that of the RC. The two controllers generated setpoint trajectories that were approximately equivalent in terms of 24-hour temperature integrals and the energy consumption resulting from these control regimes was compared. The strategy used by the RC to generate setpoints was to force the 24-hour temperature integral as closely as practicable to a given target value. This target (for a given day in the year) was that which would be obtained if the day temperature were to be constant at 21°C and the night temperature at 17°C. It was calculated as suggested by de Koning (1988b), based on the lengths of the day and of the night. The latter were derived with standard solar engineering equations.

In its control strategy, the RC kept the daytime heating setpoint constant at 21°C and manipulated the nighttime setpoint in its attempt to achieve the target. This was done because the temperature achieved in the greenhouse was not necessarily always the same as the controller's setpoint. For example, there can be overheating during sunny periods and this has to be compensated for (de Koning 1988b). For the night setpoint trajectory the RC calculated a new heating setpoint for every five minute period. This was based on the temperature integral achieved up until then (calculated starting from the beginning of the previous daytime period), the length of the remaining night period, and the target value. The minimum allowable setpoint for the RC was kept fixed at 12°C.

The neural model

To train the ANN used by the SBC, data covering a wide spectrum of situations were produced by running simulations with the greenhouse system, using three methods of setpoint generation. The first training data set was composed of inputs and outputs of simulations for which the RC was installed and which used weather records for the first five months of 1982. For the two other data sets, the simulations were run with the same meteorological data, but the setpoints were generated randomly. This was done to make it possible to submit the ANN to various training conditions at a time when the strategy followed by the SBC had not yet been elaborated. The metereological data used were for Montreal and were obtained from Environment Canada.

The procedure employed to calculate the first set of randomly generated setpoints was similar to that used for the RC except that, at the beginning of each day, the daytime setpoint was chosen randomly between 12.0 and 24.5°C. The nighttime setpoint for that day was then calculated so as to achieve the same daily temperature integral as with the RC. For the second set of random setpoints, the procedure consisted of generating sequences of heating setpoints for various sequential periods. For each period, first, its duration was randomly chosen between 0 and 86,400 seconds. Then, it was randomly determined whether the setpoints would vary sinusoidally or be constant during the period. In the first case, both the mean and the amplitude of the sinusoid were chosen randomly, respectively within the ranges 14 to 24.5°C and 0 to 2.5°C. In the second case, the setpoint value for the period was simply randomly chosen between 14 to 24.5°C.

Various ANN configurations were tested (Lacroix 1994). The one that was found to be the best and that was used in the project was a feedforward network with three hidden layers of nine processing elements each. Two of the hidden layers were fully connected in parallel to the input layer with a sigmoid transfer function being used for one and a sine function for the other. These two parallel layers were both fully connected to the third hidden layer which was, in turn, fully connected to the output layer. The sigmoid transfer function was used for this third layer. Backpropagation learning was used for the training of the ANN, with the cumulative delta rule; training lasted 100,000 cycles.

Evaluation procedure

The RC and the SBC were installed one after the other in the simulated greenhouse system. Simulations were then executed using weather records for one-month periods from January to May for each of 1982, 1983, and 1984. The January to May season was chosen because heating is required and large meteorological variations occur from day to day. In January, it is generally cold and solar radiation intensity is low, whereas in May it can be either hot or cold, with either high or low solar radiation intensity.

Since the length of the day varies throughout the year and the day and night setpoints were not identical, the 24-hour temperature integral maintained by the RC varied slightly from one 24-hour period to the next. For this reason, it was decided that, for each day, the SBC must achieve a 24-hour temperature integral equal to the monthly average 24-hour temperature integral achieved with the RC.

SIMULATION RESULTS

The internal air temperatures and heating loads are presented respectively in Figs. 2 and 3, for days 2 to 16 of January, March, and May 1983, as predicted by the SBC's ANN and as obtained from the simulated greenhouse system with the SBC installed. The predictions of the ANN followed the patterns for both variables quite well. For example, the ANN was generally able to predict the pattern of the daily temperature and also successfully predicted when no heating was required.

In January, the temperature regime produced by the SBC (via the setpoint trajectories it had generated) was often inverted compared to that imposed by the RC. High setpoints were generated for the nights, and low setpoints for the days. This is illustrated for 1983 in Fig. 4; the same pattern was obtained for the other two years; for all three years the night setpoint was often close to 21°C. Thus, on the basis of its simulations, the SBC reckoned that in January it was generally more beneficial to maintain higher temperatures during the night, when the thermal screen was closed. There were a number of exceptions to this. For example, on the evening of January 4, (at about 90 h, Fig. 4b) the daytime setpoint was made higher than the nighttime setpoint for the next 24-hour trajectory (and this was soon thereafter reversed again). These exceptions often coincided with periods during which the outside temperature increased rapidly at night and/or at the beginning of the following day. This was the case in the

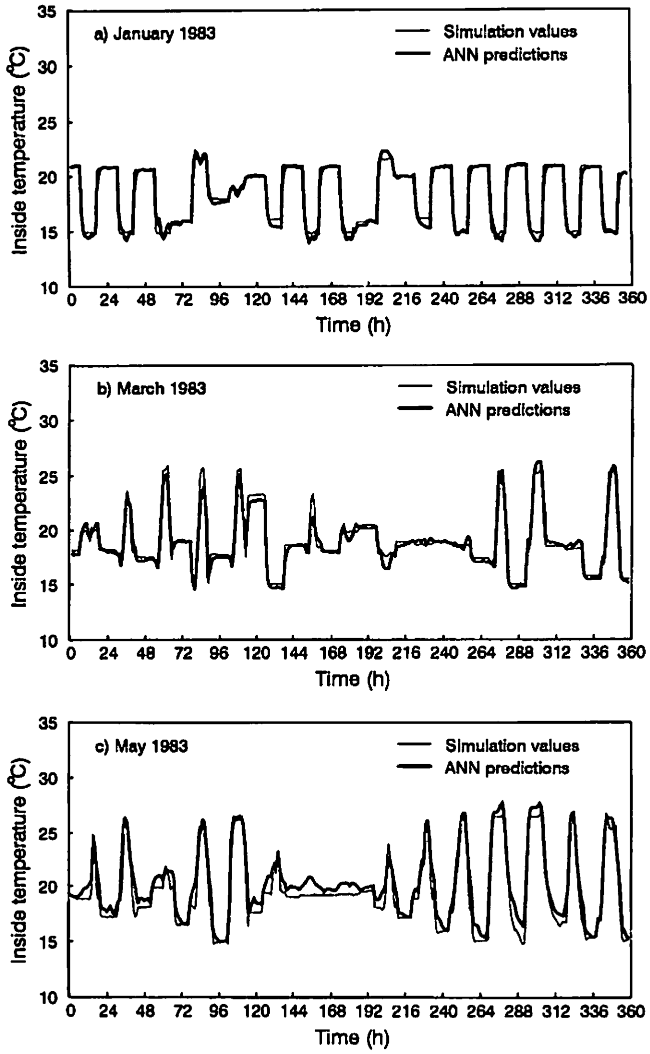

Fig. 2. Greenhouse air temperature as predicted by the SBC's ANN and as obtained from the simulated greenhouse system with the SBC installed for days 2 to 16 of January, March, and May 1983.

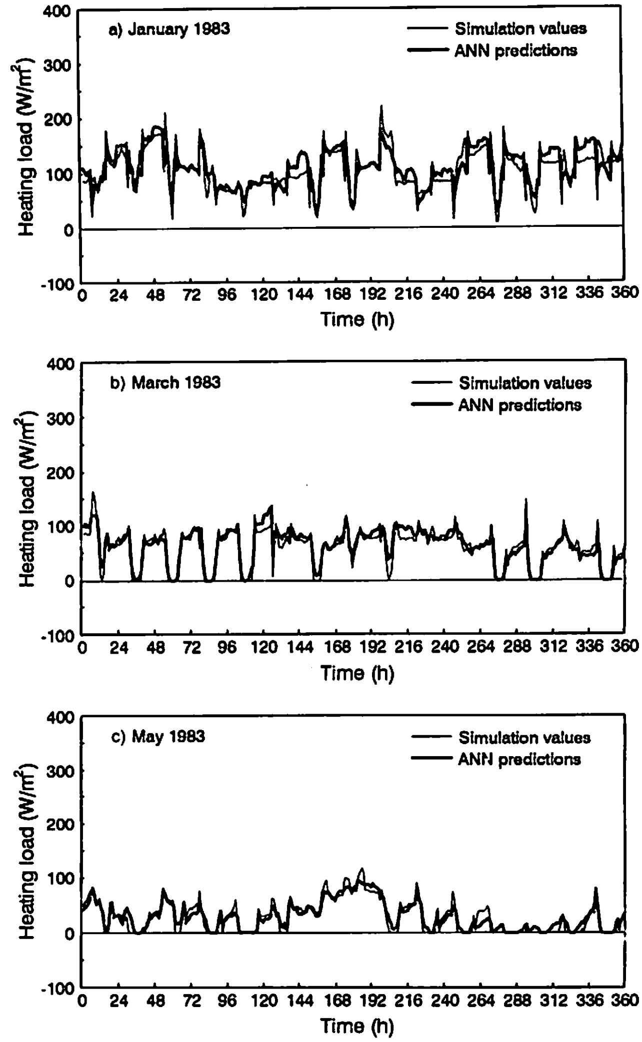

Fig. 3. Heating loads as predicted by the SBC's ANN and as obtained from the simulated greenhouse system with the SBC installed for days 2 to 16 of January, March, and May 1983.

example given; on January 5 (between about 100 h and 110 h, Fig. 4c) the outside temperature increased from -16°C early in the morning to slightly above 0°C in the middle of the day. A similar situation occurred between 220 h and 230 h. These rapid changes of the outside temperature appear to have influenced the decisions of the SBC. As is evident from Fig. 4, in January 1983 the greenhouse temperature followed the setpoints very closely and no overheating occurred. This was also true for January 1982 and January 1984.

As illustrated in Fig. 5, the setpoint regime of the SBC was more variable during the first 15 days of March 1983 than it had been during January. This was also true for the other two years investigated. For all three years, the daily differences between the daytime and nighttime setpoints generated by the SBC during March were frequently smaller than those for January (as small as 1°C and as large as 8°C). The day-to-day differences were, however, larger. Daytime overheating occurred fairly frequently (see Fig. 5b). The SBC anticipated such overheating and compensated for it by picking a low setpoint for the preceeding night. However, when both the outside temperature and the solar radiation intensity during the following day were anticipated to be relatively low, the SBC tended to maintain a high setpoint during the night (e.g., 23°C). This was observed on a number of occasions during all three years studied; it happened particularly frequently in March 1984, a month during which practically no overheating occurred.

For all three years studied, during the first 15 days of May the heating setpoints were often lower during the night than during the day. This is illustrated for May 1984 in Fig. 6. Thus, compared to the situation during January, the temperature regime was similar to that traditionally maintained in greenhouses. Overheating occurred almost every day due to the relatively high solar radiation intensity and outside temperature. Since the ANN had predicted this overheating, the SBC maintained low temperatures during the preceeding night so as compensate for this and still reach the required 24-hour temperature integral. It was also observed that with the SBC the

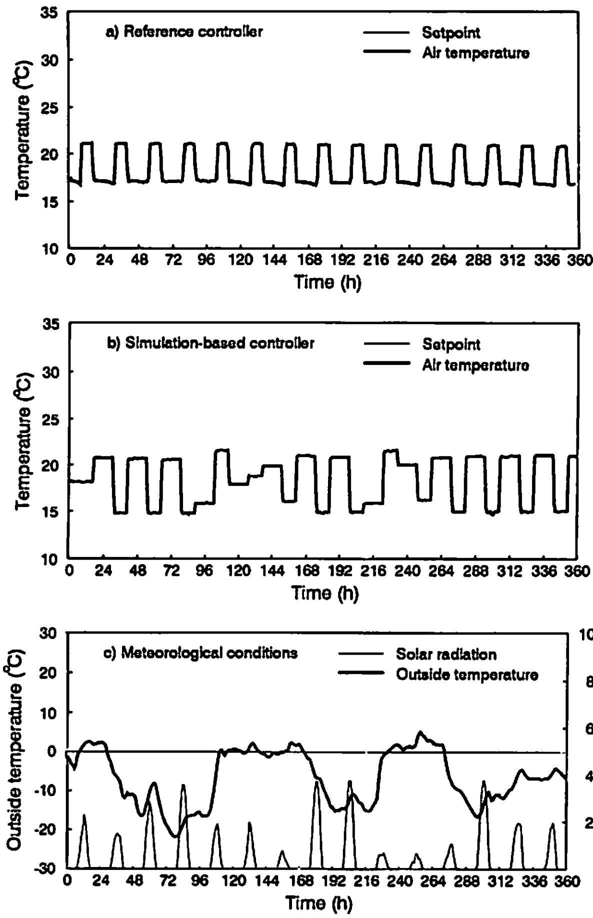

Fig. 4. Setpoints, greenhouse air temperature, and meteorological conditions for the 15 days of January 1983 (note that for parts a and b the two traces are practically coincident).

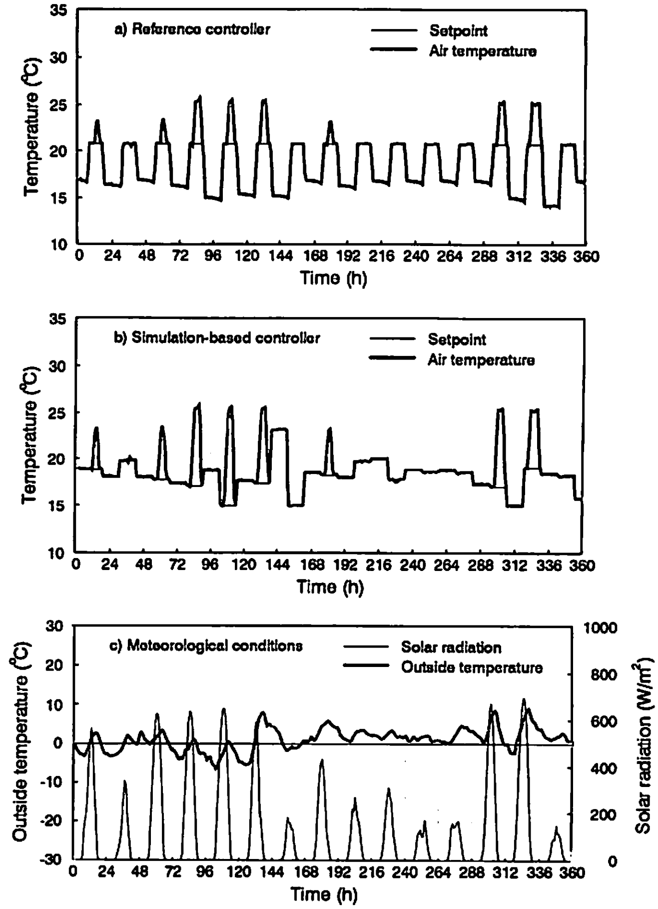

Fig. 5. Setpoints, greenhouse air temperature, and meteorological conditions for the 15 days of March 1983.

daily minimum values for the setpoints were generally higher than with the RC (Fig. 6a), even if a similar monthly average temperature was maintained by both controllers (Table II).

The monthly minimum greenhouse air temperature, the monthly average greenhouse air temperature, and the total energy consumed for heating with both the RC and the SBC are compared in Table II for all three years. The monthly maximum temperatures are not reported here. They were similar for the two controllers since they were dependent on the ventilation which, in turn, was dependent on the ventilation setpoint, which was the same for the two cases. Generally, the two controllers achieved very similar average temperatures (and, therefore, similar temperature integrals) but the SBC required 5.7 to 14.3% less energy to accomplish this. Over the five-month simulation period the total energy requirement was 7.1, 7.1 and 7.7% less for the years 1982, 1983, and 1984, respectively.

FRAMEWORK FOR SIMULATION-BASED CONTROL

Potential benefits

The SBC allowed the greenhouse system to adapt itself to the anticipated weather so that it consumed less energy than with the RC. For example, the heating energy requirement was reduced, on the average, by more than 7%. This illustrates that with the simulation-based approach it is possible to have better control than with conventional approaches such as fixing the setpoints or, for a greenhouse equipped with a thermal screen, simply inverting the heating regime. Presumably, even greater energy savings might be obtained with the same method by considering the anticipated meteorological conditions for a larger number of days so that the temperature integral could be maintained over a longer period. Another advantage of the simulation-based approach is that it maintains more appropriate setpoints than those that result from procedures such as the one used by the RC, because a more complex controller such as the SBC will not allow very low temperatures to occur.

In this project, the role of the SBC was confined to the control of temperature. Other variables might, however, also be similarly dealt with. For instance, in greenhouse control, CO_2 concentration, light intensity, curtain open/close times, and hydroponic solution composition would all be suitable as controlled variables. The same approach could be used, as well, in other types of ecosystems for the control of variables such as population levels. Simulation-based control could also be used for the actual achievement of setpoints (as opposed to their determination). For instance, it might be attractive to complement the PI control of hot water heating and ventilation systems in this way.

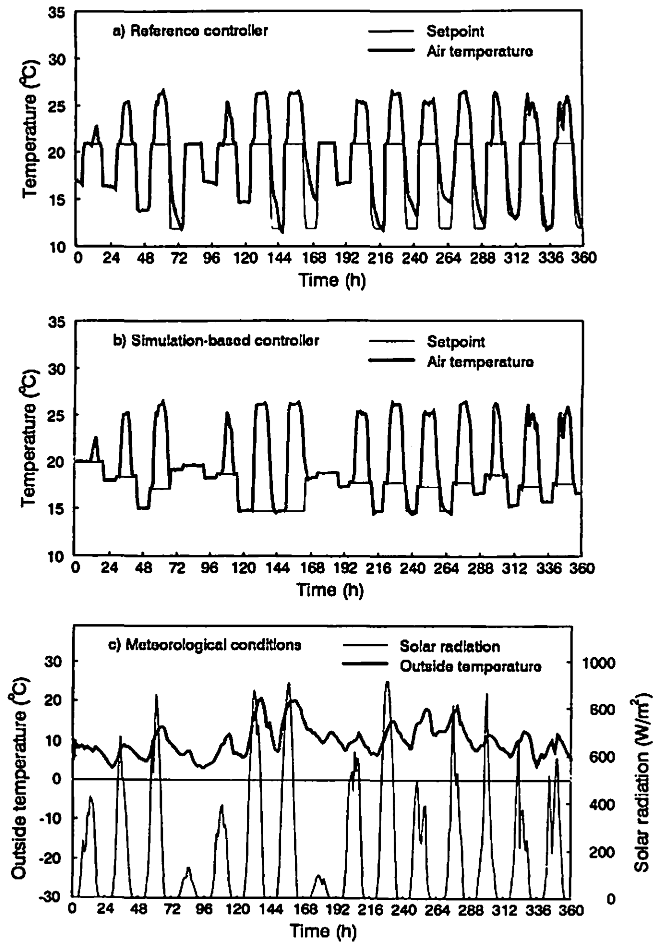

Fig. 6. Setpoints, greenhouse air temperature, and meteorological conditions for the 15 days of May 1984.

Extension to longer anticipation periods

The longer the anticipation period (i.e., the period for which conditions are predicted and analyzed), the greater the flexibility of the SBC in acting because the number of possible setpoint trajectories is directly proportional to the length of this period. Thus, the longer the period considered in the decision making, the more optimal control can be. For the situation presented here, for instance, the anticipation period might be substantially increased because the temperature integration period for mature tomato plants can be as long as a week and weather forecast bulletins are generally available for up to five days.

Elaborating control strategies over longer anticipation periods does mean, however, that the data treatment will be more complex and more calculations are required. For example, if the anticipation and temperature integration periods are increased from 24 to 48 hours and if for each 24-hour period five meteorological possibilities and 10 setpoint regimes are considered, the number of scenarios that needs to be evaluated will rise from 50 to 2500. With the approach used in this project (where up to 30 simulations may be required for each scenario), this could lead to 75,000 simulations for the 48-hour period. Now, if the anticipation period is increased further to five days, using the same approach could lead to a requirement of more than 9 billion simulations. Also, for longer anticipation periods the weather forecasts become less reliable and this should also be taken into account in the calculations. Extending the anticipation period can, therefore, potentially lead to additional benefits, but the management of the control procedure will also become more complicated.

Simulation-based multivariable control

In the control of enclosed ecosystems, the global optimum is a function of many interacting variables, quite a few of which might be externally disturbed and others that can be treated more as process parameters in that they will remain relatively undisturbed. For the greenhouse situation discussed, a number of meteorological variables and factors such as infestation, etc. fall into the first category, whereas cultivar characteristics, for example, would fall into the second one. Regardless of categorization, all of these must be taken into account simultaneously in the determination of an optimal control strategy and the entire set of relationships among them must be considered. The simulation-based approach can obviously be extended to such a multivariable situation wherein many types of disturbances are dealt with and a number of variables are manipulated at the same time.

In this project, the SBC used the heating setpoint as the manipulated variable and iterated through different setpoint regimes to choose an optimal one. By doing this, it performed a numerical optimization (although, undoubtedly, it chose a sub-optimal solution when compared to the global optimum). A similar method might be used for several manipulated variables, a very simple approach being to simply nest the loops for the variables considered. For example, if CO_2 concentration were to be considered together with temperature, different trajectories of CO_2 setpoints could be tested in combination with each possible heating setpoint trajectory. Evidently, as for the extended anticipatory period, the number of simulations required will increase rapidly for each variable added so that massive iterative calculations may be required. As pointed out, the use of neural network models for simulation can be very advantageous in this regard, when compared to procedural ones, i.e., they can yield reasonable results more than a hundred times faster (Kok et al. 1994; Shukla et al. 1996). There is however, also a limit to this and various artificial intelligence techniques might be used either to constrain the domain of investigation (e.g., rule-based reasoning methods) or to "steer" the investigation, thus further limiting simulation activity and making more efficient use of computational machinery. Constraint satisfaction techniques as those used by Cros and Martin-Clouaire (1991) for greenhouse climatic setpoints might, for example, might be beneficial in situations such as this. These various aspects all need to be investigated further in order to develop a more complete approach to multivariable control.

Artificial neural networks

In this project, ANN's proved to be an appropriate technology with which to model a system for implementation in an SBC. Although an ANN model is in some ways less flexible than a procedural one, it is usually much faster to execute, depending on the complexity of the situation being modeled, with the

Table II. Results obtained with the simulation-based controller and the reference controller for 1982, 1983, and 1984.

	Reference controller			Simulation-based controller			Diff. Energy [%]
	T_{min} [°C]	T_{avg} [°C]	Energy [MJ/m^2]	T_{min} [°C]	T_{avg} [°C]	Energy [MJ/m^2]	
1982							
January	15.6	18.4	389.1	14.6	18.3	365.7	6.0
February	15.3	18.7	255.0	14.7	18.8	234.4	8.1
March	13.1	18.9	193.6	14.8	19.1	177.8	8.2
April	11.7	19.5	131.9	14.7	19.6	123.2	6.6
May	11.7	21.5	23.6	14.7	21.5	21.4	9.3
Total			993.1			922.5	7.1
1983							
January	16.3	18.4	304.5	14.7	18.6	285.9	6.1
February	15.4	18.7	230.3	14.7	18.9	215.3	6.5
March	14.0	18.9	183.5	14.8	19.1	170.6	7.0
April	11.6	19.2	126.9	14.6	19.2	117.7	7.2
May	11.6	20.1	58.9	14.7	20.0	50.5	14.3
Total			904.2			840.0	7.1
1984							
January	16.0	18.4	334.0	14.7	18.5	314.8	5.7
February	14.8	18.6	216.8	14.8	18.8	201.8	6.9
March	13.8	18.9	250.4	14.8	19.0	227.2	9.3
April	11.7	19.5	89.9	14.7	19.6	85.4	5.0
May	11.7	20.3	53.7	14.6	20.3	48.5	9.7
Total			944.9			877.7	7.7

T_{min}: Minimum greenhouse air temperature
T_{avg}: Average greenhouse air temperature
Energy: Energy required for heating
Diff. Energy: Percentage of difference in energy required for heating between the reference controller and the simulation-based controller.

ANN's relative advantage increasing with the complexity. Its relative lack of flexibility can also be compensated for to a certain degree by appropriate configuration and training. If trained for the correct variables and domain, an ANN can be very useful indeed for numerical optimization, allowing rapid iteration through diverse contexts.

One important advantage of ANN's is that they possess the capacity to learn. Therefore, they constitute a technology that is particularly well-suited to the implementation of conscious control. In this way, the controller can relatively easily be given access to a model with which to reason about the system and its various reactions to environmental disturbances. The latter might be either real, anticipated, or merely potential. Thus, an ANN can be used to analyze a system's past decisions in past contexts, so that it can learn how to behave better when it again faces similar conditions. In other words, with the aid of other components of the SBC, like rule-based experts, the ANN (as well as the rest of the SBC) can be revised through reflection. A neural model also has the advantage that it can be continuously retrained in response to new data and thereby adapt to new situations. In this way, the ANN model approach is superior as compared, for example, to the traditional method of making least-square adjustments to the parameters of procedural models. For the latter, all data, new and old, must be fed to the re-calculation process simultaneously, while for an ANN the new data can simply be added and used for further training. If required, the training process can also be biased in favour of the most recent conditions.

A further advantage of ANN's is that they are able to model not only the controlled system, but also any control mechanisms that are included within the larger system boundary, as well as the control strategies followed by such mechanisms (e.g., Seginer et al. 1996). It therefore becomes quite simple to model and simulate the behavior of a composite system. This was done, for instance, in the work presented here; the ANN was trained to imitate the greenhouse behavior, which was affected by the ventilation setpoint as well as by the opening and closing of the thermal screen. The decision-making processes for the thermal screen and the ventilation were thus represented in the ANN.

CONCLUSIONS

Simulation-based control enables a system to prepare itself for future disturbances, if it has a notion of what they will be. Thus, the system can engage in anticipatory control. It can also investigate the effects of various control alternatives prior to their implementation and choose the actions that will best fulfill its goals. Past decisions can also be re-examined and the control system can be made self-adjusting. Hence, the implementation of simulation capacity in a control system affords many potential advantages by conferring upon the system the capacity to re-evaluate its performance and to adapt to new situations. Because it increases the adaptive capacity of a system, this approach holds considerable promise for the control of a wide variety of enclosed ecosystems.

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