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Neural Networks Models for Temperature and CO_2 Control

[1]R. Salazar, [2]U. Schmidt, [2]C. Huber, [1]A. Rojano and [1]I. López
[1]Autonomous University of Chapingo, Km 38.5 Carr,
México-Texcoco Chapingo, Edo., México, C.P 56230, México
[2]Institute for Horticultural Sciences, Humboldt-University Berlin,
Lentzeallee 55-14195 Berlin, Germany

Abstract: In this study, we are interested in regulating two important variables inside of the greenhouse: temperature and CO_2 enrichment for two cabins in a experimental greenhouse at the Humboldt University of Berlin. Predicting the behavior of these two variables and photosynthesis will allow us to turn on and off the controls such as heating system, vents opening or CO_2 enrichment at the right time, in order to save energy and keep the plants inside of the comfort zone. Artificial Neural Networks (ANN) were used because of their ability to capture the non linear relationships governing the changes in the greenhouse environment. Temperature was predicted 5 and 10 min ahead of the sensor signal, with MSE errors between measured and predicted values of 0.088 and 0.029, respectively. The CO_2 predicted from the model was used as an input in the photosynthesis model. In this last model, seven variables were used and the predictions were highly precise with a MSE errors of 0.0563 and 0.0974 for photosynthesis 5 and 10 min ahead, respectively. A sensitivity analysis was performed in the photosynthesis model showing that relative humidity is an important variable for CO_2 levels and for the photosynthesis process. The predicting models will allow to achieve our final goal which is to replace the sensors and give predictive information for a higher control quality in an open loop control system.

Key words: Greenhouse, neural networks, prediction, environmental conditions

INTRODUCTION

Greenhouse cultivation helps to create favorable microclimates where production of vegetables and flowers is made possible through out the year or part of the year as per the requirement. The greenhouse technology has also tremendous scope in horticultural sector, especially for production of hybrid seeds, high value vegetables, ornamental and medicinal plants (Kumar *et al*., 2006). However, the quantity and quality in greenhouse crop production can be realized only if the growth factors are managed so, they are available to the plant at the right time with desired amounts (Portree, 1996). In fact, according to Hanan (1998), enriching greenhouse just to maintain CO_2 concentrations of 335 ppm (34 Pa) can increase output and value of long season tomato crops by as much as 10% with report in yield increases to 4 kg m^{-2}. Regulating these environmental factors to the benefit of the greenhouse crop is part of good greenhouse management. The effect of temperature on tomato growth and its measurement is strongly linked to climatic factors such as humidity,

Corresponding Author: R. Salazar, Autonomous University of Chapingo, Km 38.5 Carr, México-Texcoco Chapingo, Edo., México, C.P 56230, México

radiation, wind velocity and CO_2 concentration. The last factor can limit growth because it is required for photosynthesis (Nederhoff and Vegter, 1994).

Single control algorithms with separated control loops are not able to manage the micro climate complexity. The interaction between microclimate factors and plant responses needs data processing and a predicting tool of some variables for process control purposes. A combination of new control methods based on Artificial Intelligence (AI) technology with multi layer structures of control systems was presented several years ago (Hashimoto, 1997; Morimoto *et al*., 1996). Another strategy for operating with predictive algorithms is the integration of micro climate models into the control system shown by Schmidt (1996). This in part reflects the fact that research is still revealing shortcomings in the quantitative understanding of some processes.

Due to the fact that greenhouse system is considered as a nonlinear, multivariable, nonstationary system and open to exterior environment (Bennis *et al*., 2008), the black box models have been successfully used in this kind of problems like Artificial Neural Networks (ANN) which according to Chen *et al*. (2008) are useful when the rules are unknown and it allows good fits to complex multivariate data.

Artificial Neural Networks (ANN) excel at uncovering patterns or relationships in data and are also powerful non-linear estimators. Because of its empirical nature, ANN technology is sometimes erroneously referred to as an advanced type of regression analysis. However, regression treats all output variables independent of each other, the presence of common arcs in the ANN architecture allows it to identify important inter-relationships that may exist between output variables (Hecht-Nielsen, 1987).

Artificial Neural Networks (ANN) have been use widely in agriculture, examples can be found by Patel *et al*. (1998), detecting blood defects in eggs with a high precision of 91.1%. Also, Kalogirou (2000) showed many ANN applications in energy problems showing that ANN is a robust and tolerant method to white noise which is very convenient for energy problems.

Seginer (1997) used Neural Network models for optimal environmental control and he found that NN models relieves the difficulty involved in finding a physical model which relates ventilation rate to outside conditions.

Linker *et al*. (1998) extended the use of Neural Network Models by not only fitting models to experimental data, but also by using them to optimize the greenhouse operation. A data based greenhouse model was developed and incorporated in an optimization scheme to compute optimal temperature and CO_2 concentration set points as a function of the changing weather. This study indicated that the models used not only fitted the data well but also produced reasonable optimization results to control the greenhouse environment.

The final purpose of the climate control is to minimize the production cost in energy and raw materials but at the same time to have good quality products. In this particular study, we want to control temperature and CO_2 enrichment inside of the greenhouse. Three models are developed, the first one is the temperature model, our concern is the temperature variations inside of the greenhouse, a good quality temperature sensors are still very sensitive to door openings and other factors so there is a need to eliminate this noise and to know the actual temperature trend in order to turn off/on the heating or cooling system, so the inside temperature is predicted 5 and 10 min ahead of the sensors reading.

The second and third model are linked, first we predict CO_2 concentrations 5 min in advance to be used in the third model for the purpose of photosynthesis prediction. Given that CO_2 injection is very expensive we do not want to apply CO_2 when photosynthesis is decreasing. These two actions will result in money and energy savings.

MATERIALS AND METHODS

A Multi-Layered Perceptron (MLP) network with a hyperbolic function was used in this work for the three models mentioned above. The performance measure is the Mean Square Error (MSE) given by Eq. 1:

$$MSE = \frac{1}{Tn}\sum_{t=1}^{T}\sum_{j=1}^{n}(y_j^t(\text{data}) - y_j^t(\text{ANN results}))^2 \tag{1}$$

Where:
MSE = Mean square error
T = Total No. of data
n = No. of output variables
y_j = Output variables

The software package MATLAB Neural Networks Toolbox was used to train, validate and test the ANN prediction models.

Temperature Model

This particular study was developed in a experimental venlo-style glass greenhouse (Cabin 6) at Humboldt University of Berlin. The greenhouse is 9.6 m width by 12 m long, 4.1 m height until ridge, the ratio of the roof vent opening compared to roof area is 50%, floor space is 115.2 m^2 with 128 tomato plants (8 times 18). Sensors for all of the inside environmental variables were located in the center of the greenhouse at a height of 1.5 m for the period of study.

According to Kumari *et al*. (2006), the temperature fluctuation inside of the greenhouse plays an important role for plant health. Therefore, thermal heating inside of the greenhouse should be minimum, which implies to maintain a good temperature control close to the optimum levels. So, the set points for temperature where fix in 18°C to start the heating system and 27°C to activate ventilation.

Data were collected every 5 min (this is the time step) from October 2007. The input variables for the temperature model were: outside average air temperature (T_{ex}, °C), outside relative humidity (RH_{ex}, %), solar radiation (SR, W m^{-2}), wind velocity (WV, m sec^{-1}), inside relative humidity (RH, %), inside air temperature 5 min lagged and actual temperature (T_{t-1}, T_t, °C), vents opening left (V_{left}, %) and right (V_{right}, %), average temperature in the heating system in the top (HS_{top}, °C) and the bottom (HS_{bottom}, °C) calculated as the average between temperature of the water in the inlet and outlet in the heating system. The variables used in the output layer were inside air temperature measured 5 and 10 min ago (T_{t+1}, T_{t+2},°C).

A total number of 7800 data points were available, of which 50% were used for training, 25% for verification and 25% for testing (Swingler, 2001). During training, data patterns were processed through the ANN until a minimum acceptable error between measured and predicted values in Eq. 1 was achieved. It was at this point that the ANN had learned to predict the system behavior of interest (i.e., values of output variables) in response to the values of the input variables.

CO_2 Model

As shown in Fig. 1a-e, for some periods where there are good conditions for photosynthesis (temperature, PAR), there is not enough CO_2 supply (red arrows) to increase

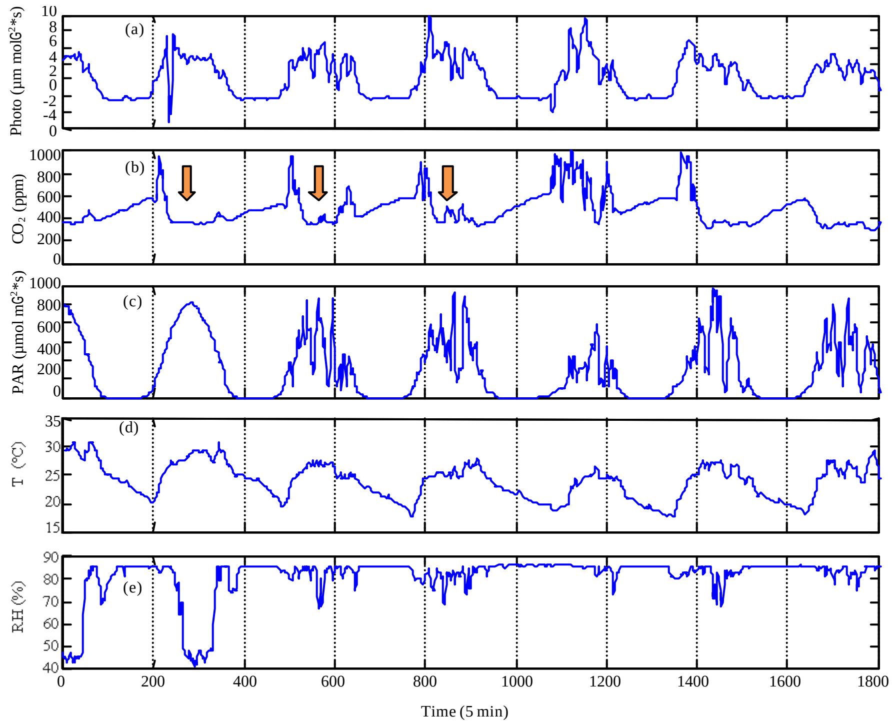

Fig. 1: (a-e) Variables behavior inside of cabin 2 June 2008

photosynthesis, so it is necessary to improve the CO_2 control by having a good prediction of both variables, in this way, we can stop the CO_2 injection when necessary. Leaks in the greenhouse allow a continuous infiltration of outside air. An average value for infiltration in a glass house would be one air change h^{-1} (Blom *et al*., 2002); therefore outside CO_2 concentration (CO_{2ext}, ppm) and wind velocity (WV, m sec^{-1}) are included as an input variables in the model.

Data was recorded every 5 min from June 2007 for Cabin 2. This Cabin have the same characteristics as Cabin 6, but with CO_2 enrichment. The experimental greenhouse has three pipes on the floor for CO_2 enrichment, each pipe is 10 m long and they are uniformly distributed, the CO_2 valve is open every time the CO_2 level is below 250 ppm in which case a gas rate of 10 lt min^{-1} is released. The CO_2 valve is closed when CO_2 level inside of the greenhouse is 1000 ppm.

The variables used in the input layer for the CO_2 model are: outside average air temperature (T_{ex}, °C), outside CO_2 concentration (CO_{2ext}, ppm), solar radiation (SR, W m^{-2}), wind velocity (WV, m sec^{-1}), inside temperature (T, °C), inside CO_2 (CO_2, ppm) and inside relative humidity (RH, %), vents opening left (V_{left}, %) and right (V_{right}, %). The output layer has only one variable: inside CO_2 concentration 5 min ahead (t+1), 50% of the data was used for training, 25% for verification and 25% for testing. An additional data set of 200 values were used to test the performance of the Neural Network model. For this particular set of data the outside CO_2 concentration varies from 306-498 ppm while the inside CO_2 concentration varies from 283-1097 ppm.

Photosynthesis Model

Carbon dioxide is an important factor for the photosynthesis process, it enters into the plant through the stomata openings by the process of diffusion. The stomata represents the prime passageways for the escaping water vapour. At the same time the stomata are the entrance openings for CO_2. By closing their stomata, plants are in a position to cut down the water loss, however stomata closure has a harmful consequence for photosynthesis as the CO_2 supply is also cut (Ehlers and Goss, 2003). To account for the stomata openings we measure stomata conductance at the leaf surface under natural conditions, a cuvette is clamped to the leaf and the environmental factors are recorded and mimicked inside the cuvette.

For this particular study, the device for photosynthesis measurement is the PTM-48M photosynthesis, an automatic four channel open type system for monitoring CO_2 exchange and transpiration leaves. Leave cuvetts are fix at the first full developed leave at the top for measuring photosynthesis. In the open photosynthesis system the CO_2 exchange is determined on the basis of the depression of CO_2 concentration at the outlet (CO_{2out}) of the leaf chamber in comparison with the incoming ambient air (CO_{2in}). The CO_2 exchange rate is calculated in Eq. 2:

$$CO_{2ER} = K(CO_{2in} - CO_{2out})F \tag{2}$$

Where:

CO_{2ER} = CO_2 exchange rate
F = Air flow rate through leaf cuvette ($m^3\ h^{-1}$)
k = Dimension factor (depends on pressure and temperature and is calculated automatically)

Photosynthesis is calculated taking into account the air flow rate through leaf cuvette ($m^3\ h^{-1}$) and the CO_2 molar mass and density.

The output from CO_2 model was used as an input in the photosynthesis model. However, given that photosynthesis is measured every 15 min we applied linear interpolation to generate two additional points, in this way we can have a point every 5 min as the rest of the data in order to fulfill uniformity. As in the CO_2 model, data from Cabin 2 were used every 5 min from June 2007 at the experimental Venlo-style glass greenhouse at the Humboldt University of Berlin. The variables used in the input layer are: inside air temperature (T_t, °C), inside CO_2 concentration (CO_{2t}, ppm), inside relative humidity (RH_t, %), stomata conductance (STcond), Photosynthetically Active Radiation (PAR_t, µmol m^{-2}*s), actual and 5 min lagged photosynthesis ($Photo_t$, $Photo_{t-1}$). The output in the model is the photosynthesis predicted 5 and 10 min ahead of time ($Photo_{t+1}$, $Photo_{t+2}$).

RESULTS

The Neural Network model for temperature prediction was trained, validated and tested and the algorithm converges after 103 iterations with a low mean square error of 0.0025. The optimal ANN architecture has 3 layers, the input layer with 11 nodes (input variables), the hidden layer with 9 nodes and the output layer with 2 nodes (prediction variables). A linear regression was performed between measured and predicted temperature values for times 5 and 10 min ahead (t+1 and t+2) and the correlation coefficients were 0.997 and 0.994, respectively. This model was able to predict temperature 5 and 10 min ahead of the sensor

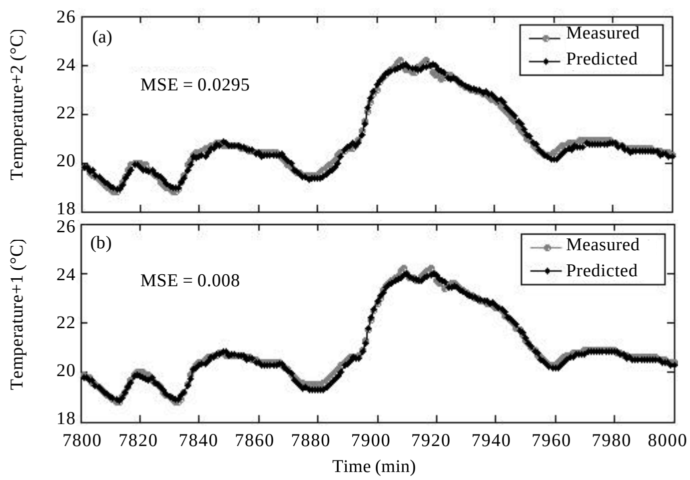

Fig. 2: (a, b) Temperature predictions using a different data set. NN predictions cabin 6 October 2007

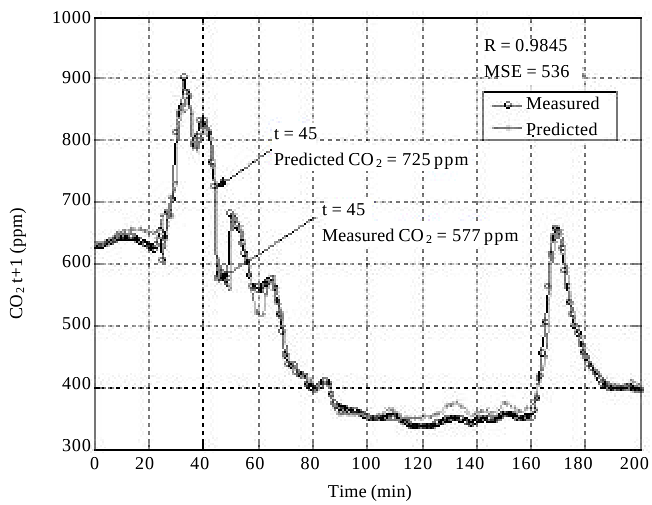

Fig. 3: CO_2 predictions using a different data set. One day CO_2 predictions cabin 2 June 22, 2008, 3:20-19:55 h (5-100 min)

signal simultaneously. In order to test the performance of the model a new data set was feed into the ANN model, only the input data was provided. Figure 2a and b show the simulation results, the MSE´s between measured and predicted temperature values were 0.008 and 0.0295 for the temperature 5 and 10 min ahead, respectively.

For the CO_2 model the algorithm converges after 82 iterations with a low mean square error of 0.00332. Again a linear regression was performed between measured and predicted CO_2 values 5 min ahead (t+1) with a correlation coefficient of 0.9845. The ANN was feed with an additional 200 input data without providing the output variables, Figure 3 shows the results, the MSE´s between measured and predicted CO_2 values was 535, which is a big value compared with the results obtained for temperature model. Sometimes, the measured values increase or decrease so rapidly while the predictions from the model are smooth, for these particular case there is a single row in the data set which make a big contribution to the MSE error (Fig. 3).

The predicted CO_2 values were used as an input for the photosynthesis model together with the other input variables. The ANN model for photosynthesis prediction converges after 82 iterations with an MSE error of 0.004922. The performance of the ANN model was tested with 150 different data set, for two cases: for measured and predicted CO_2 values as an input data, the first case is shown in Fig. 4a and b and the second case in Fig. 5a and b. There is a small difference between the two cases but the MSE`s errors decrease when the predicted CO_2 values are used as an input data. As for the other models a linear regression was performed between measured and predicted values for the two cases resulting in

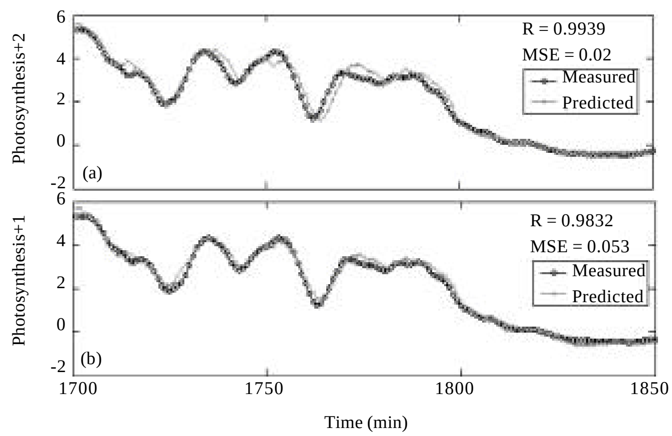

Fig. 4: (a, b) Photosynthesis predictions using predicted CO_2 from ANN model. Predictions using predicted CO_2 cabin 2 June 6, 21:35 to June 7, 10:05 h, 2008

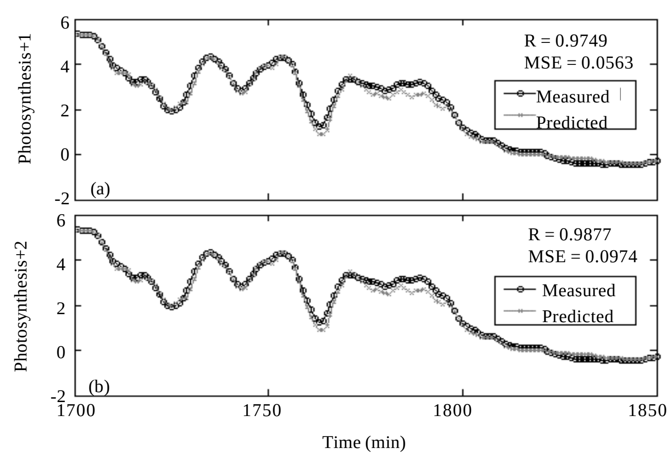

Fig. 5: (a, b) Photosynthesis predictions using measured CO_2. Predictions using measured CO_2 cabin 2 June 6, 21:35 to June 7, 10:05 h, 2008

correlation coefficients slightly bigger when measured CO_2 values were used instead of the predictions from NN model (Fig. 4, 5a and b).

Photosynthesis is a complex process which depends on so many variables specially temperature (°C), CO_2 (ppm), PAR (µmol m^{-2}*s) and relative humidity(%). The maximum photosynthesis (9.6 µmol m^{-2}*s) occurs when temperature (24.8°C), relative humidity (78.3%), PAR (663.55 µmol m^{-2}*s) and CO_2 (577 ppm) are in good levels. For instance when PAR is maximum (1177.6 µmol m^{-2}*s) and temperature is 27.2°C, the photosynthesis is only 4.29 µmol m^{-2}*s, because the CO_2 level is low (364 ppm). On the other hand, when CO_2 level is maximum (1001 ppm) and relative humidity is high (86.1%), but PAR (323.15 µmol m^{-2}*s) and temperature (22.6°C) are not in the optimal levels, then photosynthesis is 8.09962 µmol m^{-2}*s. A sensitivity analysis was performed for the photosynthesis model (Table 1) and the most important variables for the prediction were the photosynthesis itself and relative humidity. Finally, Fig. 6 and 7 show the pathway for photosynthesis depending

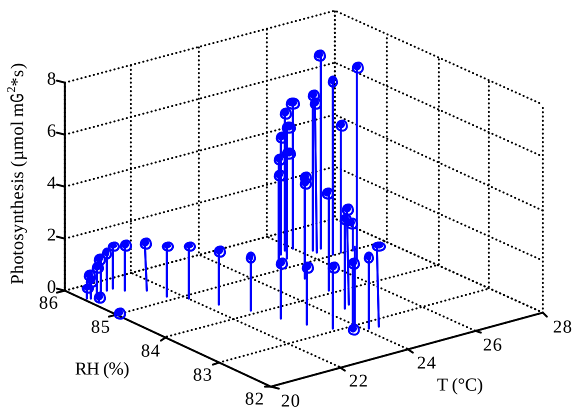

Fig. 6: Photosynthesis pathway depending on temperature and relative humidity. Photosynthesis pathway (June 10 from 4:50 am)

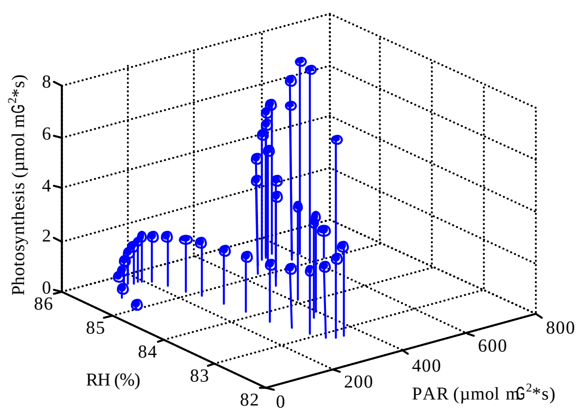

Fig. 7: Photosynthesis pathway depending on PAR and relative humidity. Photosynthesis pathway (June 10 from 4:50 am)

Table 1: Sensitivity analysis for photosynthesis model

Alternatives	R (t+1)	R (t+2)	MSE (t+1)	MSE (t+2)
Without photosynthesis in time t-1	0.977	0.964	0.260	0.400
Without photosynthesis in time t and t-1	0.904	0.912	0.757	6.035
Without photosynthesis (t-1) and temperature	0.903	0.912	0.703	0.619
Without photosynthesis (t-1) and relative humidity	0.910	0.903	0.924	9.927
Without photosynthesis (t-1)and PAR	0.842	0.841	0.585	0.554
Without photosynthesis (t-1) and stomatal conductance	0.908	0.916	0.568	0.443
Without photosynthesis (t-1) and CO_2	0.903	0.910	0.793	0.695

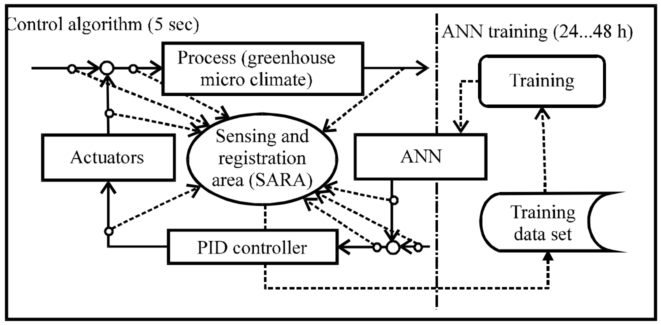

Fig. 8: Predictive open loop control with artificial neuronal networks

on relative humidity and temperature and on relative humidity and PAR respectively, high levels of photosynthesis are related with high levels of relative humidity.

CONCLUSIONS

Three Neural Network models were successfully developed for temperature, CO_2 and photosynthesis prediction in two experimental greenhouses located at the Humboldt University of Berlin. For the temperature model we use cabin 6 which is the control cabin naturally ventilated with tomato crop. The temperature predicting model was able to predict temperature 5 and 10 min ahead of the sensor signal with high precision.

A data set from cabin 2 with CO_2 enrichment was used for the CO_2 and photosynthesis prediction models for June 2007. The predictions of the CO_2 model were acceptable, the measured and predicted values follows the same tendency, however the MSE error was not small (535) because of the big changes in the measured CO_2 in one point, but in general the model provide accurate results.

On the other hand, the photosynthesis model was tested with measured and predicted CO_2 values as an input data, in both cases the model provides highly precise results with a slightly differences, given the best results when predicted CO_2 is used as an input variable. According to the sensitivity analysis relative humidity is an important variable in the photosynthesis process. Our final goal is to use the predicting models in an open loop control system (Fig. 8) and the ANN could both replace the sensors and give predictive information for a higher control quality. An essential prerequisite is an intermittent running of the training process so that the ANN can adapt to changing's in the technical and biological constraints.

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