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Contributed article

Development of a neural network heating controller for solar buildings

A.A. Argiriou[a,*], I. Bellas-Velidis[b], C.A. Balaras[a]

[a]*Institute for Environmental Research and Sustainable Development, Group Energy Conservation, National Observatory of Athens, I. Metaxa & V. Pavlou, GR-152 36 Palaia Pendeli, Greece*

[b]*Institute for Astronomy and Astrophysics, National Observatory of Athens, I. Metaxa and V. Pavlou, GR-152 36 Palaia Pendeli, Greece*

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Abstract

Artificial neural networks (ANN's) are more and more widely used in energy management processes. ANN's can be very useful in optimizing the energy demand of buildings, especially of those of high thermal inertia. These include the so-called solar buildings. For those buildings, a controller able to forecast not only the energy demand but also the weather conditions can lead to energy savings while maintaining thermal comfort. In this paper, such an ANN controller is proposed. It consists of a meteorological module, forecasting the ambient temperature and solar irradiance, the heating energy switch predictor module and the indoor temperature-defining module. The performance of the controller has been tested both experimentally and in a building thermal simulation environment. The results showed that the use of the proposed controller can lead to 7.5% annual energy savings in the case of a highly insulated passive solar test cell.

Keywords: Artificial neural networks; Heating system control; Solar buildings; Neural controllers; Energy management; Ambient temperature forecasting; Solar irradiance forecasting; Feed forward back propagation

1. Introduction

The use of artificial neural networks in various applications related to the energy management has been growing significantly over the years. Current applications not only are related to energy demand forecasting (Han, Xiu, Wang, Chen, & Tan, 1997; Khotanzad et al., 1997), but also include heating, ventilation and air conditioning systems of buildings (Curtiss, Kreider, & Brandemuehl, 1993; Kreider, 1995). The results have revealed the potential usefulness of artificial neural networks for the energy management of individual houses or small residential buildings (Bellas-Velidis, Argiriou, Balaras, & Kontoyannidis, 1998; Kanarachos & Geramanis, 1998).

Artificial neural networks (ANN's) can be very useful in optimizing the energy demand of buildings, especially those having high thermal mass (and therefore an important time constant) and systems that maximize the use of solar energy for space heating. For the so-called solar buildings, a controller being able to forecast the energy demand but also the weather conditions can lead to energy savings, while maintaining acceptable indoor conditions. The controller decreases the potential of overheating, usually observed in this type of building during days with highly variable solar radiation availability and passive solar gains.

The aim of this paper is to investigate the performance of ANN's, in order to control the indoor temperature of a solar building. The following sections present an overview of the design concept for the artificial neural network-based controller and its theoretical and experimental performance assessment.

2. Concept of the controller

Buildings consume about one third of the total final energy in the industrialized world, for heating, cooling, ventilation, lighting and services. Therefore, worldwide efforts have concentrated on developing new systems and techniques to increase energy savings by the rational use of energy in the building sector.

The controller presented in this paper is intended for single-family solar houses. The term "solar" implies that the house exhibits the following general characteristics, compared to ordinary type of constructions:

- Reduced thermal losses, by improving the building envelope thermal performance (i.e. increased thermal insulation, double glazing, reduced air infiltration).

* Corresponding author. Tel.: +30-1-803-2503; fax: +30-1-613-8343. *E-mail address:* thanos@astro.noa.gr (A.A. Argiriou).

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Nomenclature

C_f	cost-function
E_a	final status (ON or OFF) of the heating energy system
E_s	heating energy system status prediction from the inverse model
N_d	day of the year
N_h	hour of the day
S_r	global solar irradiance
T_i	indoor air temperature
T_o	ambient air temperature
T_s	indoor air temperature setpoint
δT	allowed maximum deviation for T_s
Superscripts	
+	forecasted value

- Increased direct solar gains, through passive solar features of glazed surfaces like windows and sunspaces, that significantly reduce the heating load by collecting and storing solar thermal energy.

The energy consumption of a building to reach the desirable indoor thermal comfort conditions depends on the thermal characteristics of its envelope and on the local climatic conditions. However, not all the weather parameters have the same impact on the heating energy consumption of a building. Accordingly, the solar irradiance and the ambient air temperature, rather than other weather parameters mostly influence solar houses, provided with the general features described above.

Solar irradiance is a parameter that can vary significantly in time and space. The time scale of these variations can be as short as of the order of some minutes. This variability is usually observed during spring and autumn, depending on the geographical latitude of the location. The majority of heating systems in buildings operates by a simple thermostatic control. This type of control can lead to overheating periods during the day, since the controller can not forecast neither the evolution of the weather conditions nor the reaction of the building under a certain weather excitation. The term overheating implies that the building indoor air temperature exceeds the desirable thermal comfort levels because of an increase of the solar heat gains. As a result, there is a twofold negative impact causing indoor thermal discomfort and energy waste from the operation of the heating system. Alternatively, a controller having the ability to forecast, up to a certain extend, the weather parameters and also their impact to the thermal behaviour of the building, can reduce the energy required for maintaining the indoor conditions within the thermal comfort zone. For example, if properly accounted for, the predicted daily variation of solar radiation availability in the morning can be used to control the heating system in such a way as to avoid the anticipated overheating in the afternoon. Neural networks exhibit features that allow them to learn and reproduce the behaviour of data time series. This fact together with the adaptive character of some of the ANN's provides them with the necessary features that an intelligent controller should have, that is achieve rational use of energy while maintaining thermal comfort.

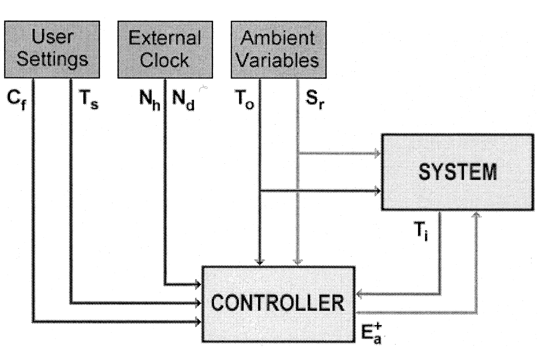


Fig. 1. Solar house heating system controller set-up (C_f: cost function; T_s: indoor air temperature set-point; N_h: hour; N_d: day of the year; T_o: ambient air temperature; S_r: Solar irradiance; T_i: indoor air temperature; E_a^+: heating energy required during the next time period).

Having in mind that a controller to be widely used must be reasonably priced, it has to have the strict minimum of input requirements. Accordingly, the input parameters for the new controller were selected to include the solar irradiance (S_r), the ambient temperature (T_o), and the indoor temperature (T_i), as illustrated in Fig. 1. These inputs are measured in regular time intervals, set at 15 min. This time interval allows the controller not to loose information even in the case of a fast responding building. Based on the values of the input parameters at a given time step and their history, the controller output is an estimate of the status (ON or OFF) of the heating energy system required by the building during the next time interval. The controller optimally (e.g. by minimizing some cost function (C_f) maintains the T_i within the thermal comfort zone set by the user. An example of such a cost function is linear combination of the energy savings achieved and the thermal comfort obtained.

This paper presents the design and test results of an artificial neural network controller for a simple ON/OFF electrical heating system. The controller has a modular structure

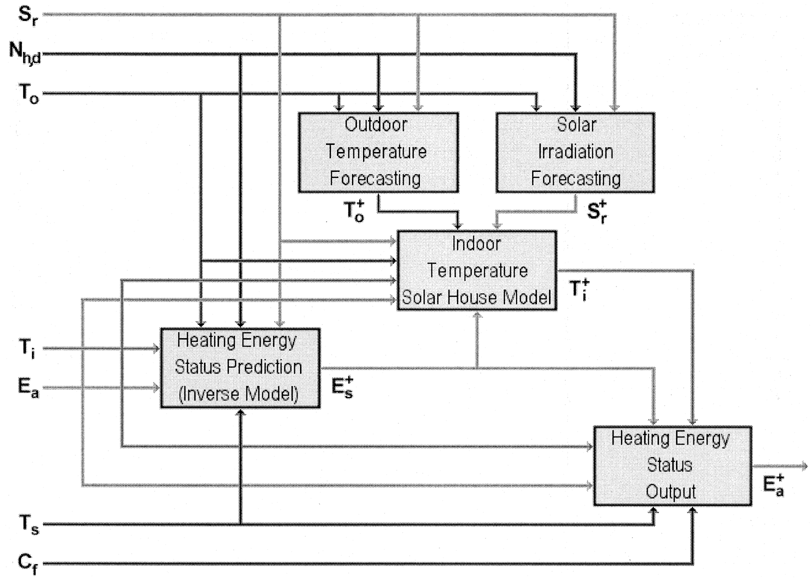


Fig. 2. The modular structure of the developed ANN controller. (S_r: solar irradiance; $N_{h,d}$: Day and hour; T_o: ambient air temperature; T_i: indoor air temperature; E_a: heating energy required by the building; T_s: indoor air temperature set-point; C_f: cost function; E_s: operation status of the heating system. The symbol (+) on the exponent of the above values, denotes their predicted values for the next time step).

illustrated in Fig. 2, with separate modules to perform the various required tasks. Two modules perform the weather forecasting; one predicts the S_r and the other the T_o, using the values of these parameters at the previous time steps and parameters characterising the specific time interval (hour N_h, and day N_d).

A third module predicts the ON/OFF operation status of the heating system, E_s. It uses as inputs the measured actual and the last six time-steps values of the solar irradiance, ambient and indoor temperature, and status (on or off) of the heating system. This module is trained to act as the inverse model of the system, i.e. the combined thermal behaviour of the building and the electrical heater. This module forecasts if during the next time step, depending on the values of the aforementioned parameters, the electrical heaters will be set on or off.

The parameters S_r, T_o, and E_s predicted by the above three modules and their corresponding past values, as well as the past T_i and E_a are passed to the fourth module that estimates

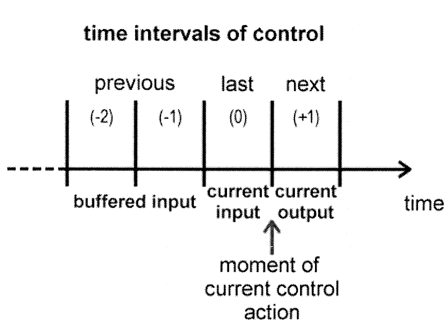


Fig. 3. Definitions of the input/output data sequences.

the indoor temperature T_i for the next time step. This module is the internal model of the system.

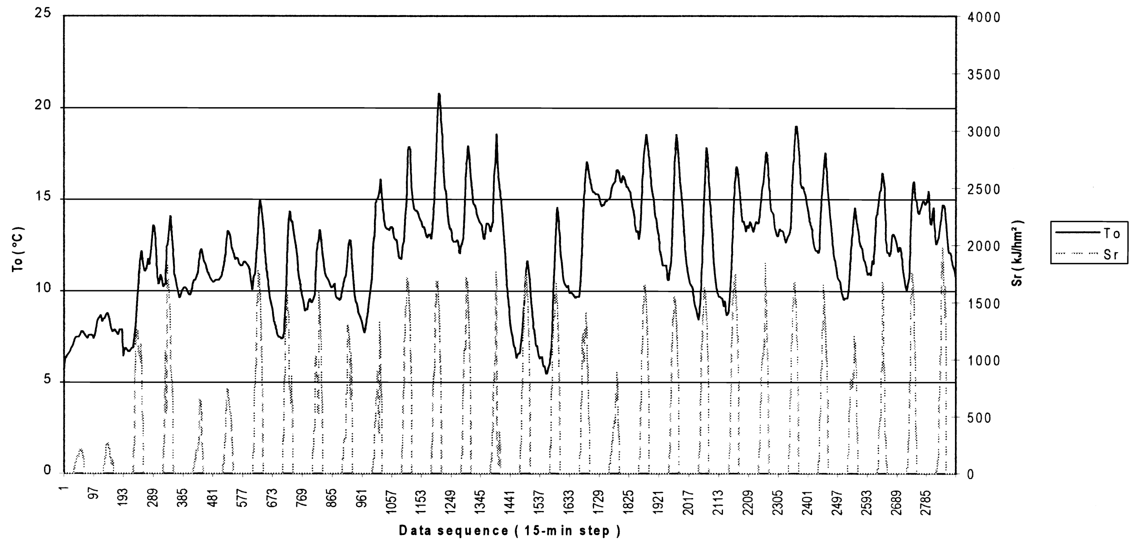
These four modules are created by applying an Artificial Neural Network (ANN) algorithm, namely the Feed Forward Back Propagation (FFBP) model. Supervised training with the method of Back Propagation with Momentum Term was used. The various ANN modules were developed under the Stuttgart Neural Network Simulator software package (Zell et al., 1995).

The last module defines the final output from the controller to the heating system, that is the E_a ON/OFF switch position. The module uses the last and the predicted values (T_i, E_s) for the controller to decide on the next status E_a. The decision is taken by applying the following simple logic rules:

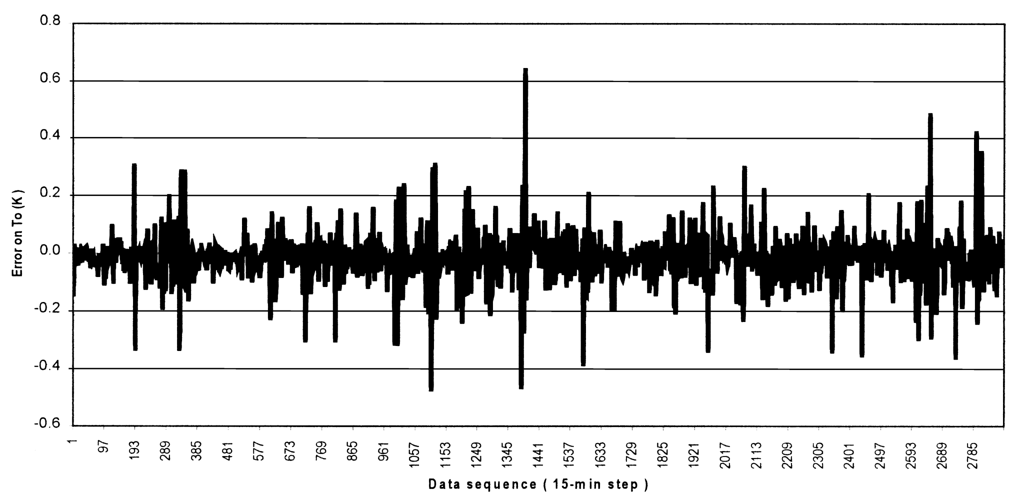
If $E_s+ = \text{OFF}$ and $T_i+ < T_s - \delta T$ then $E_a+ = \text{ON}$
If $E_s+ = \text{ON}$ and $T_i+ > T_s + \delta T$ then $E_a+ = \text{OFF}$
In all other cases $E_a+ = E_s+$.

There is one additional module (not shown in Fig. 2) that performs the necessary I/O functions and internal buffering of the parameters. The input gives the last time interval parameters, whereas the buffer keeps the six previous intervals values, and the output is the control action for the next time step (Fig. 3).

It should be noted that numerical test, during the development of the various modules showed that a one-step ahead forecast is satisfactory for the performance of the particular controller. This was confirmed during the in situ experimental testing of various controller versions.



(a)



(b)

Fig. 4. Results of the off-line tests for the forecasting of solar irradiance (S_r) and ambient temperature (T_o). (a) Measured values; (b) Error in T_o; (c) Error in S_r.

3. Artificial neural network modules

3.1. Weather forecasting

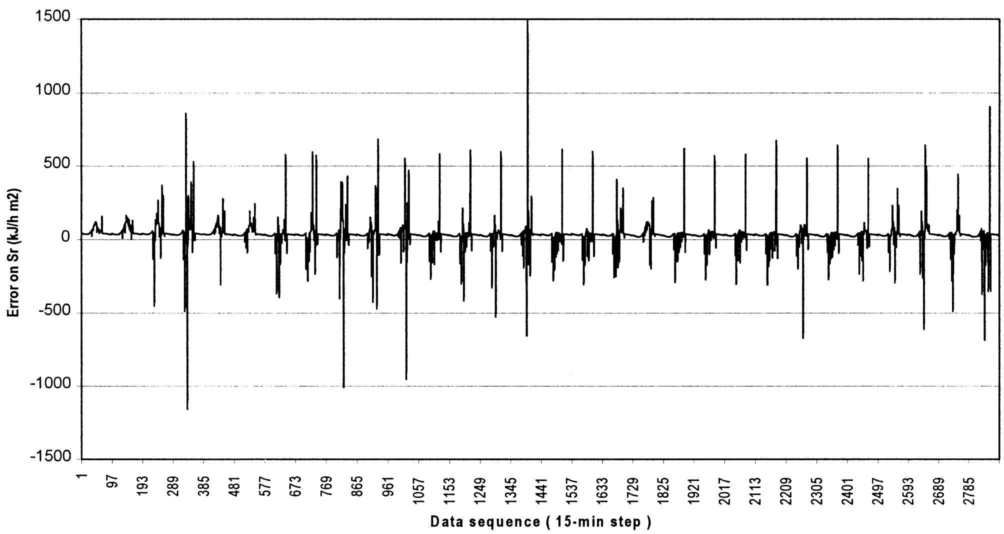
The module forecasting the outdoor temperature uses a simple ANN. It has 10 input neurons, one hidden layer of eight and another of four neurons, and one output neuron. The inputs to this ANN are:

$N_h^{(+1)}$ the (daily normalised) time value for the next interval;
$T_o^{(0,-1,-2,-3)}$ the last and three previous values of the outdoor temperature;
$N_d^{(+1)}$ the (yearly normalised) day number for the next interval;
$S_r^{(0,-1,-2,-3)}$ the last and three previous values of the solar irradiance.

Hourly values are normalised by dividing them by 24 and the day number values by 365. Also all other parameters are normalised to fit in the interval [0,1].

The output is the one-step ahead prediction $\Delta T_o = T_o^{(+1)} - T_o^{(0)}$ This is the outdoor temperature difference for the next time step. This ANN was trained using part of real meteorological data for 1993 in Athens, Greece, collected by the National Observatory of Athens. The rest of the data were used for verification during the training. Additional data for three years, from 1994 to 1996, were also used in off-line tests.

The solar irradiation forecast module uses similar FFBP architecture and training procedure, but the number of neurons is higher due to the more complicated behaviour of this parameter. Also, test showed that the ANN performs better when including time delay values for N_h and N_d. The



(c)

Fig. 4. (*continued*)

ANN has 28 input neurons, one hidden layer of 16 and another of eight neurons, and one output neuron. The inputs are the last and six previous values of the following parameters:

$N_h^{(0,-1,-2,-3,-4,-5,-6)}$ daily normalized time;
$T_o^{(0,-1,-2,-3,-4,-5,-6)}$ ambient temperature;
$N_d^{(0,-1,-2,-3,-4,-5,-6)}$ day of the year;
$S_r^{(0,-1,-2,-3,-4,-5,-6)}$ solar irradiance.

The output is the one-step ahead prediction $\Delta S_r = S_r^{(+1)} - S_r^{(0)}$, that is the difference of the global solar irradiance for the next interval.

The training/verification/testing of this ANN were performed using the respective data of the same time series as for the ambient temperature forecasting module.

Representative test results of the two modules are shown in Fig. 4. The difference between the real and the forecasted (one-step ahead) outdoor temperature rises up to 1 K in just a few cases (Fig. 4b). However, the prediction of solar irradiance is not so accurate. The difference (Fig. 4c) shows a correlation with the hour of the day, the differences being important at low solar angles, i.e. close to sunrise and sunset. The prediction error is about 10–20% for clear sky days. It should be noted that in any case most building apertures would not even see the sun at these times so the errors do not affect the controller much.

Given the limited number of input parameters of the proposed controller, the performance of the weather forecasting modules can be considered acceptable, especially when compared with results from previous works. Santamouris, Mihalakakou, Psiloglou, Eftaxias, and Asimakopoulos (1999) for example use an ANN model with a considerably higher number of inputs, i.e. ambient air temperature, ambient relative humidity, sunshine duration and extraterrestrial irradiance. Despite the complexity of their configuration, they report errors up to 14%.

In addition, the on-line tests under real operating conditions, discussed in Section 4, demonstrate that the indoor temperature responds slowly to abrupt weather changes. Therefore, the prediction errors of solar irradiance do not jeopardise the overall performance of the controller.

3.2. The heating energy predictor module (inverse model)

This module is implemented by modifying the previously investigated heating energy predictor (Bellas-Velidis et al., 1998). This ANN has 35 input neurons, one hidden layer of 15 neurons and an output layer of one neuron. The data set used to train/verify/test this ANN was prepared with the TRNSYS (a building thermal simulation software) model of the PASSYS Test Cell and weather data described above. The inputs to the ANN module are the previous and last six values of the following parameters:

$N_h^{(0,-1,-2,-3,-4,-5,-6)}$ daily normalized time;
$S_r^{(0,-1,-2,-3,-4,-5,-6)}$ solar irradiance;
$T_o^{(0,-1,-2,-3,-4,-5,-6)}$ ambient temperature;
$T_i^{(0,-1,-2,-3,-4,-5,-6)}$ indoor temperature;
$E_a^{(0,-1,-2,-3,-4,-5,-6)}$ real status of the heating system.

The single output is one-step ahead prediction $E_s^{(+1)}$ of the heating system status for the next time step.

3.3. The indoor temperature-defining module (internal model)

It is an internal model of the system, i.e. it provides the indoor temperature (T_i) for a given time step. For this, it uses

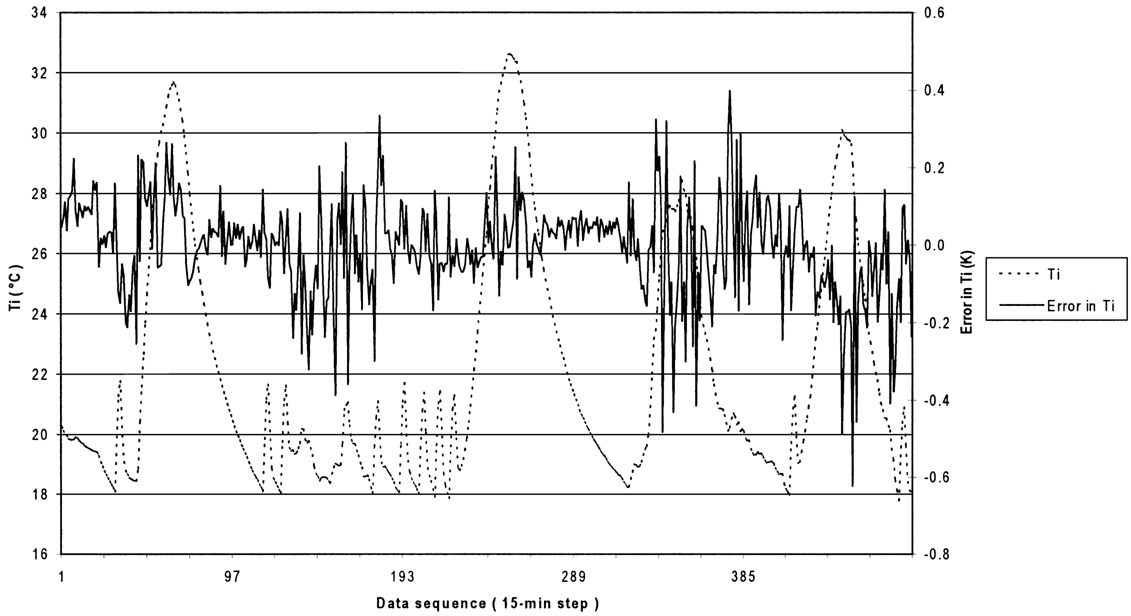


Fig. 5. Offline test results for the forecasting of the indoor temperature.

the values of the external parameters (T_o, S_r, E_a) acting on the system at the current and at previous intervals, as well as the previous internal state. The ANN used in this module has 12 input neurons, two hidden layers, the first of 12 and the second of six neurons, and one output neuron. The data used to train/verify/test this ANN module was taken from real measurements on the PASSYS Test Cell (Vandaele & Wouters, 1994). The data were collected during a two-month period (January 1st to February 28th, 1999).

The inputs of this ANN-based internal model are:

$S_r^{(+1)}$ solar irradiance at the next time step (predicted);
$T_o^{(+1)}$ outdoor temperature at the next time step (predicted);
$E_s^{(+1)}$ heating system status at the next time step (predicted);
$\Delta S_r^{(+1)} = S_r^{(+1)} - S_r^{(0)}$ predicted difference in solar irradiance;
$\Delta T_o^{(+1)} = T_o^{(+1)} - T_o^{(0)}$ predicted difference in the outdoor temperature;
$\Delta E_a^{(+1)} = E_a^{(+1)} - E_a^{(0)}$ predicted change in the status of the heating energy system;
$T_i^{(n=0,-1)}$ the last and the previous values of indoor temperature;
$\Delta T_i^{(0)} = T_i^{(0)} - T_i^{(-1)}$ last difference of the outdoor temperature;
$\Delta S_r^{(0)} = S_r^{(0)} - S_r^{(-1)}$ last difference of solar irradiance;
$\Delta T_o^{(0)} = T_o^{(0)} - T_o^{(-1)}$ last difference of the outdoor temperature;
$\Delta E_a^{(0)} = E_a^{(0)} - E_a^{(-1)}$ last difference in the heating system status;
$E_a^{(0,-1,-2,-3,-4,-5,-6)}$ last and six previous values of the heating system status.

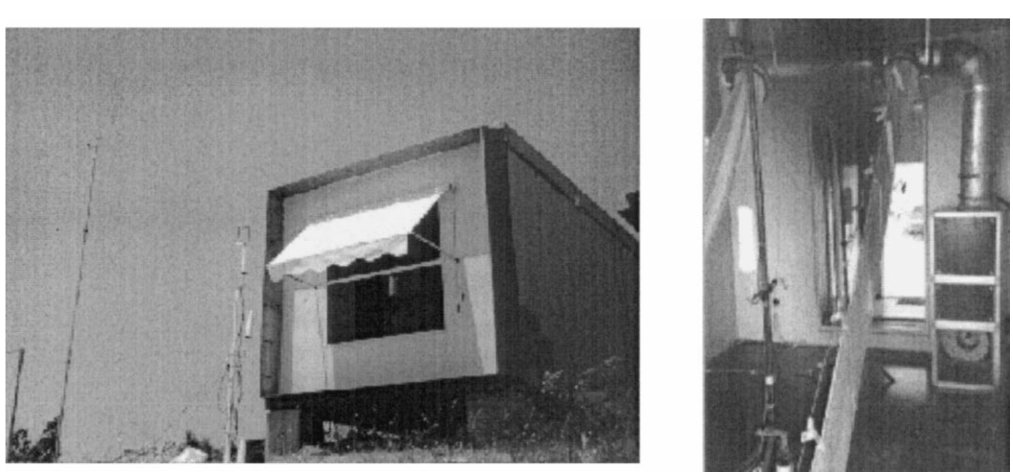


Fig. 6. The PASSYS test cell: outdoor view of the cell (left) — indoor test room (right).

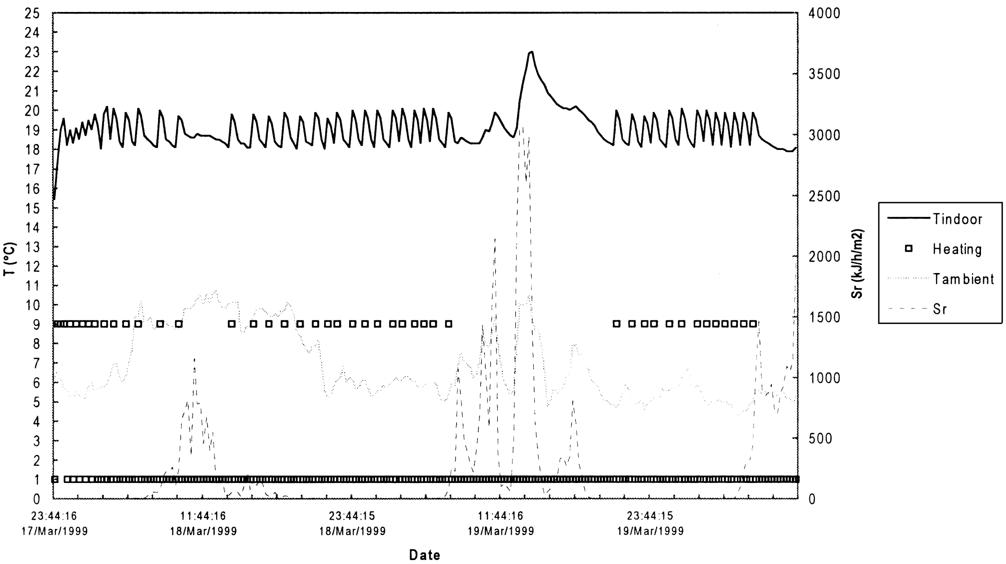


Fig. 7. Results of the in situ testing of the ANN controller (Heating System Status: 1 = OFF, 9 = ON).

The single output is the one-step ahead prediction of the indoor temperature difference for the next time step, $\Delta T_i = T_i^{(+1)} - T_i^{(0)}$.

The offline tests showed very good performance of the ANN-based internal model. Using real data, the difference between the indoor temperature given by the ANN-module and the real one (illustrated in Fig. 5, but note that the difference is shifted to 35° for illustration purposes) shows an error of about ±0.2 K.

4. Controller implementation and on-line tests

The prototype neural controller has been tested in the PASSYS test cell, located at the premises of the National Observatory Athens in Pendeli. The experimental facility is shown in Fig. 6. The test room is heated via an air heating system that has four electric resistances and a fan. During the actual operation mode, a controller activates or deactivates these resistances. The thermal mass of the test cell was altered in order to perform the experiments under more realistic conditions.

The data acquisition system was connected to the following sensors:

- Seven Pt 100 platinum resistance thermometers measuring the indoor temperature at various points inside the test room.
- One Pt 100 thermometer measuring the ambient temperature. All the thermometers are shielded against radiation.
- A CM3 Kipp and Zonen pyranometer, measuring the global horizontal solar radiation on top of the test cell.

For the needs of the current experiment, the data acquisition system controls also the heating system. All sensors are interrogated every minute and 15-min averages are stored and fed to the neural controller. The controller then decides whether the heating system should be activated or not. The data acquisition system records also the controller decision, the status of the switch that activates the heating system and the energy consumed by the heating system. The acquisition of all these parameters allows the detection of possible failure of the hardware to follow the instructions of the controller (this event occurred only twice within an almost three-month testing period and was due to power failure).

The data acquisition and control (DAC) is programmed for the above-described tasks, using an object oriented programming software. This software allows the user to easily implement other custom made applications. The controller was implemented by translating the controller algorithms into a C-code. The DAC software launches the executable of this code every 15 min. The acquired data is provided as an input to the controller code. The result of the controller activates a switch that turns the power supply of the electrical resistances on or off accordingly.

All the described ANN modules (see Section 2) are individual routines, called by a main program. A very helpful feature for this case is the ability of the Stuttgart Neural Network Simulator to transfer the trained neural networks in the form of C-functions. Without applying any optimisation of the code, the size of the executable is 233 KB. It executes almost instantly giving the necessary output.

The controller was tested in situ for three months (from December 22nd 1998 to March 30th 1999). Part of the obtained results is shown in Fig. 7. This figure shows the variation of the indoor and ambient temperature, solar irradiance and the status of the heating system ("9" indicates that the heating system is ON and "1" that the system is

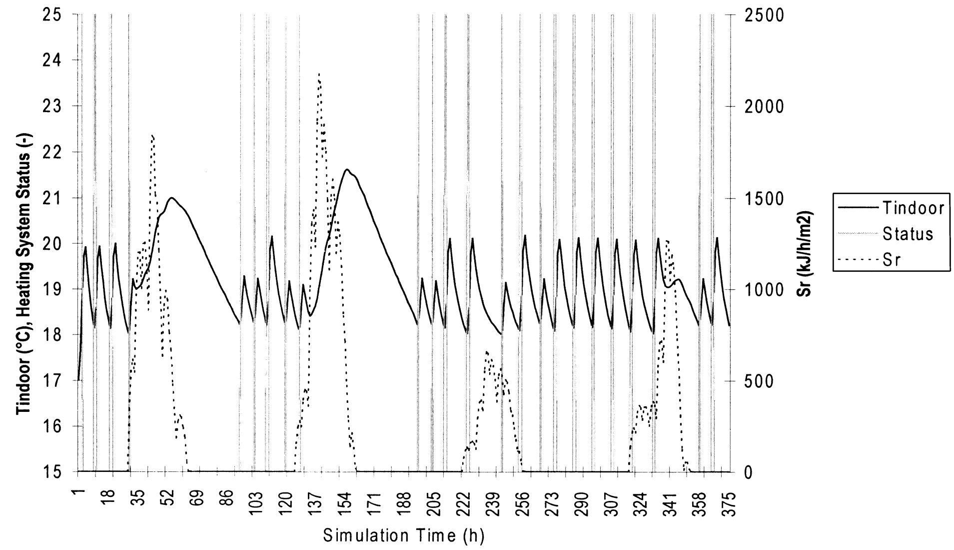


Fig. 8. Test cell performance simulation with the ANN controller.

OFF). The desirable indoor temperature range was set at 18–20°C. Accordingly, one can conclude that the developed controller maintains well the indoor temperature within the desired interval. Although the forecasts of the ambient temperature and solar radiation are not so accurate, as discussed in Section 3.1, the impact on the performance of the controller is not significant, since the set temperature range is maintained.

5. Off-line performance assessment

The performance of the neural controller over a complete heating season and its comparison with a conventional controller was performed via numerical simulation. The thermal performance of the PASSYS test cell was simulated using the well-known transient simulation code for solar systems and buildings, TRNSYS (Klein, 1994). The advantage of TRNSYS is its modularity. It is therefore possible to create a new routine with the ANN controller algorithms and apply it to the heating system of the cell. The simulation time step is identical to the actuation interval of the controller (i.e. 15 min). The meteorological data used is the Typical Meteorological Year for Athens, Greece (Argiriou et al., 1999). Two annual simulations were made: one assuming that the temperature inside the test cell has to be maintained within the range 18–20°C by a conventional controller and a second during which the temperature is kept within the same range using the

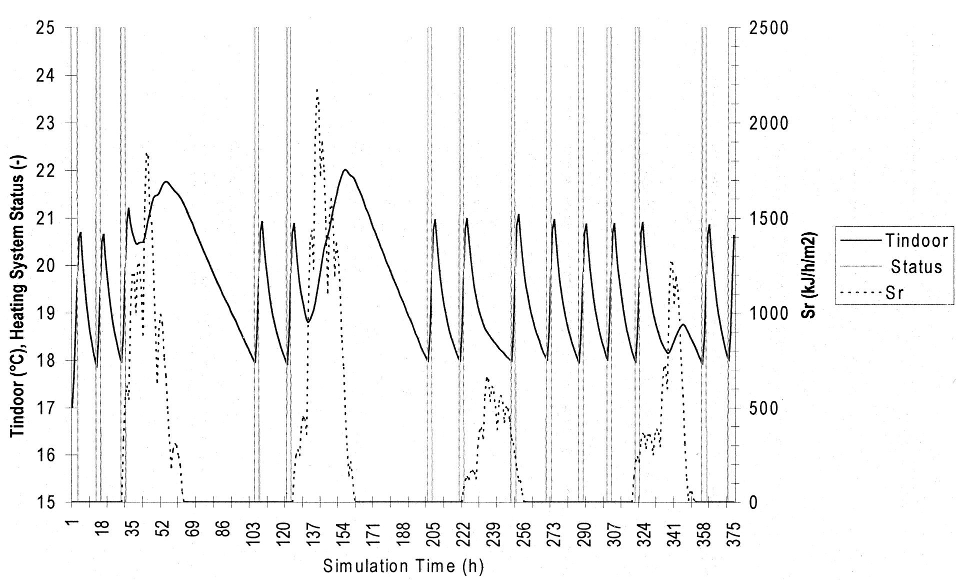


Fig. 9. Test cell performance simulation with the conventional controller.

ANN controller. The goal of these simulations is to test whether the implementation of the ANN controller reduces the energy consumption, while maintaining the indoor temperature within the desirable range.

Fig. 8 shows the indoor temperature variation for the first four simulation days (solid black line) with the ANN controller. The dashed line shows the variation of the global solar irradiance on a horizontal plane and the grey line shows the status of the heating system of the cell ("0" indicates that the heating system is OFF and "25" that the system is ON). Fig. 9 shows the corresponding data using the conventional controller for the simulation.

The comparison of the two figures leads to the following observations:

1. In both cases the lower set point of 18°C is well maintained.
2. Although the conventional controller stops the heating system at 20°C, the indoor temperature always exceeds this value. This is due to the fact that the conventional controller cannot predict and therefore it does not take into account the thermal inertia of the test cell. In some cases, the indoor temperature exceeds 21°C, even at times when solar irradiance is zero or very low. The neural controller switches-off the heating system at about 19°C, when the solar irradiance is zero or very low, "knowing" that the temperature will increase to the upper set-point of 20°C, due to the thermal inertia of the system. When the ANN controller forecasts also the increase of solar radiation, it might stop the heating system even at 18.6°C.
3. The conventional controller maintains the heating system on for about three time steps (i.e. 45 min in average), while the ANN controller does the same for about two time steps in average.

The above observations explain why the ANN controller can reduce heating energy consumption. Simulations showed that the total annual energy consumption of the test cell is 771 MJ with the conventional controller and 713 MJ with the ANN controller. Accordingly, the use of the neural controller can lead to a 7.5% decrease of the annual heating energy consumption of the PASSYS test cell.

The controller has been designed for solar buildings, i.e. for buildings that have large south oriented openings and a significant thermal mass. However, these kinds of features are also characteristic in many Southern European buildings. Surveys for the heating energy consumption in real buildings have shown that the average annual value is about 300 MJ m^{-2}. Assuming that a single house has an average floor surface of 150 m^2 and that the neural controller would result to the same percentage of energy savings as for the test cell, this leads to a reduced annual heating energy consumption of about 3.4 GJ. Taking into account that the European average electricity tariff for domestic use is about 0.18 Euro kWh^{-1}, this leads to a payback period of the complete system in about 4 years. This payback period is of the same order of magnitude as that of various proposed retrofit actions, for energy savings in buildings. Accordingly, it can be justified that the proposed controller can be also cost effective.

6. Conclusions

Experimental analysis and numerical simulations have shown that artificial neural networks can be used for a better control of the heating system in solar houses. In order to produce a low cost system, the number of input parameters was kept to a minimum and limited to the indoor and ambient temperature and horizontal solar irradiance. However, the resulting annual energy savings can be significant. This is due to the fact that the forecasting capabilities of neural networks, related to both the weather parameters and the thermal behaviour of the building, allow the shut down of the heating system prior to the actual overheating period, thus achieving optimum energy use. The application of this technique for the control of hydronic heating systems in individual houses appears to also be promising, but needs a similar analysis to quantify the anticipated results.

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