



A neural network controller for hydronic heating systems of solar buildings

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Received 29 November 2002; accepted 9 July 2003

Abstract

An artificial neural network (ANN)-based controller for hydronic heating plants of buildings is presented. The controller has forecasting capabilities: it includes a meteorological module, forecasting the ambient temperature and solar irradiance, an indoor temperature predictor module, a supply temperature predictor module and an optimizing module for the water supply temperature. All ANN modules are based on the Feed Forward Back Propagation (FFBP) model. The operation of the controller has been tested experimentally, on a real-scale office building during real operating conditions. The operation results were compared to those of a conventional controller. The performance was also assessed via numerical simulation. The detailed thermal simulation tool for solar systems and buildings TRNSYS was used. Both experimental and numerical results showed that the expected percentage of energy savings with respect to a conventional controller is of about 15% under North European weather conditions.

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Keywords: Artificial neural networks; Heating system control; Hydronic systems; Neural controller; Energy savings; Feed forward back propagation; Thermal simulation

1. Introduction

The range of applications of artificial neural networks (ANNs) is constantly increasing. Their use in applications related to energy management started in the early 1990s. Kalogirou (2001) provides a comprehensive overview of ANN applications in renewable energy systems and in buildings. ANNs appear to be particularly suited to control the heating systems of solar buildings. The thermal behaviour of solar buildings is mostly influenced by the solar irradiance and ambient temperature and it involves large time constants. Therefore, a controller having the ability to forecast up to a certain horizon these 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 comfort zone.

The need of forecasting is shown in Fig. 1 (Kummert, 2001), showing the typical behaviour of a building with important solar and internal heat gains, during a sunny mid-season day. This situation can be encountered in a passive solar building or a modern commercial building with large south-facing windows. If there is no cooling plant, overheating can occur during a sunny afternoon, despite the fact that heating has been required in the morning. If overheating occurs then it is too late to take a control decision for the heating plant: the heat stored in the building structure cannot be removed. A reduction of energy consumption would have certainly been achieved if the temperature rise had been forecasted, in order to prevent unnecessary heating during the morning hours.

Argiriou, Bellas-Velidis, and Balaras (2000) presented an ANN controller for buildings with such forecasting capabilities. It consisted of a meteorological module, forecasting the ambient temperature and solar irradiance, a heating energy predictor module and the indoor temperature-defining module. The controller was applied to a simple ON/OFF electrical heating system. The performance of

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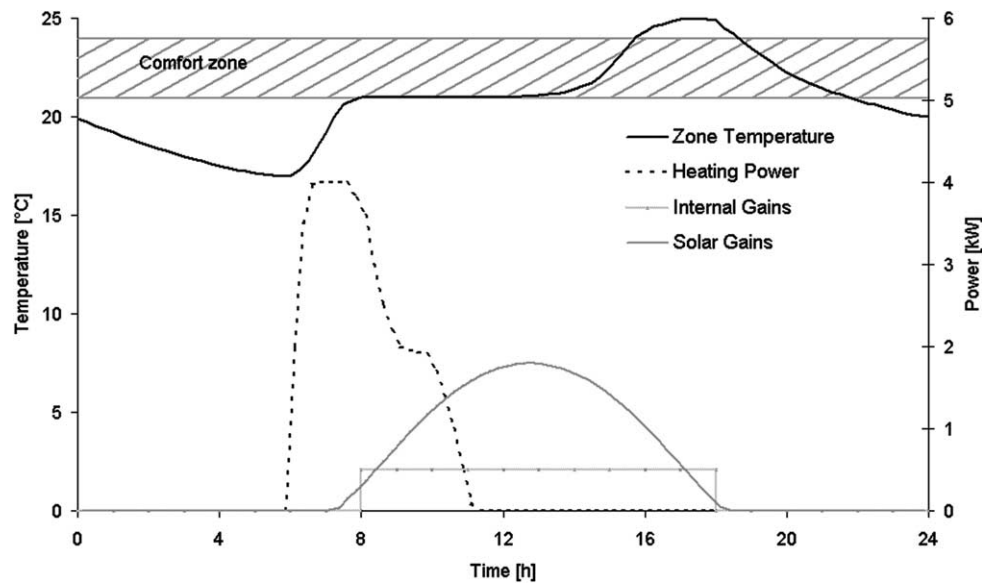


Fig. 1. Typical passive solar building behaviour on a sunny day.

the controller was tested experimentally, in the PASSYS outdoor test facility (Vandaele & Wouters, 1994) and in a building thermal simulation environment. It was found that when applied to the PASSYS test building cell, a 7.5% decrease of the annual heating energy consumption was achieved, under the weather conditions of Athens, Greece. The usefulness of that work was mainly to demonstrate the feasibility and the importance of forecasting capabilities of a heating system controller. In practice the applications of such ON/OFF control devices are limited, since the majority of residential buildings use hydronic heating plants. Therefore, it would be interesting to extend the above control concept to hydronic heating systems too. Kanarachos and Geramanis (1998) proposed an ANN for the control of single zone hydronic heating systems. The inputs and outputs of this controller included parameters related to the heating plant and the indoor set-point temperature. No forecasting of either weather parameters or indoor conditions was performed.

The present paper describes the further development of the concept proposed by Argiriou et al. (2000) and its application for the control of hydronic heating systems. The controller was realized and tested experimentally in two rooms of an office building. The following sections present the design concept of the controller and its performance assessment—experimental and in simulation environment. The structure and the development of the controller is presented in Section 2. Section 3 describes the criteria applied for the performance assessment of the controller. The performed experiments and their results are described in Section 4. Since the experimental period could not cover the complete operating season of the heating plant of a building, numerical simulations were required in order to assess the annual behaviour of the system. The simulation

results are presented in Section 5. The conclusions of this work are given in Section 6.

2. Description of the controller

The inputs to the controller are: N_d (yearly normalized), day number (1–365); N_h (daily normalized), hour (1–24); T_{amb} , ambient air temperature; G_s , solar irradiance on the south vertical plane (i.e. solar radiation impinging on a south facing vertical plane); T_i , indoor air temperature; T_s , water supply temperature (temperature of water supplied to the radiators by the boiler of the heating plant); T_r , water return temperature (temperature of water returning to the boiler). The controller aims to maintain the indoor conditions as defined by the user via some cost function (J) and the indoor air temperature set-point (T_u). The set-up of the controller and its modular structure are shown in Fig. 2. It includes a meteorological module, forecasting the ambient temperature and solar irradiance, an indoor temperature predictor module, a supply temperature predictor module and a supply temperature optimizing module. This last module calculates the final output from the controller to the heating system, i.e. the forecasted water supply temperature for the next time step, taking into account the user set point, T_u and the requirements for energy savings as given by the cost function J . The controller operates with a 15-min time step.

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 various modules were optimized via extensive off-line training. The optimization procedure included the selection:

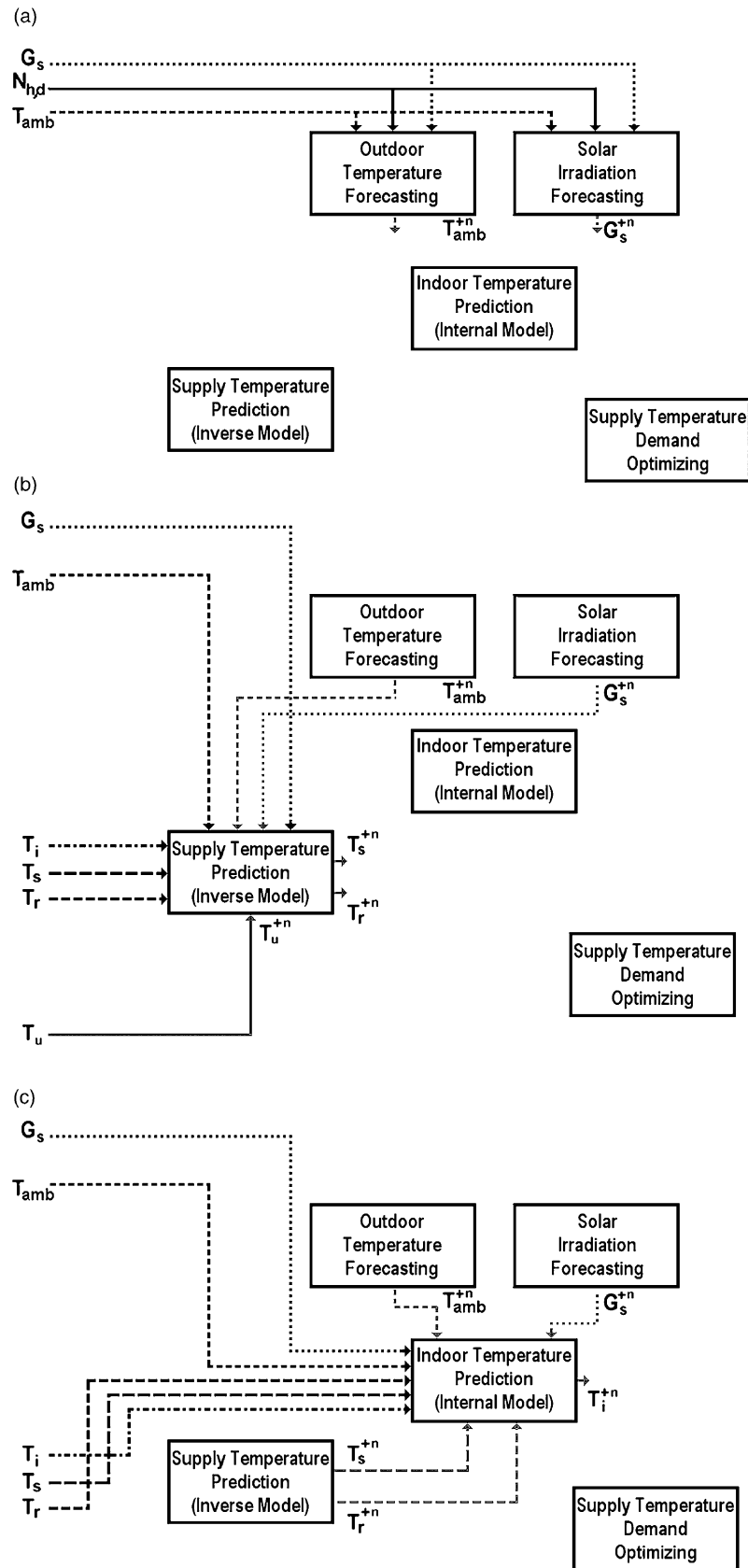


Fig. 2. Flow chart of the ANN controller: (a) weather forecasting, (b) prediction of heating system supply temperature, (c) prediction of indoor temperature, (d) optimization of heating system supply temperature.

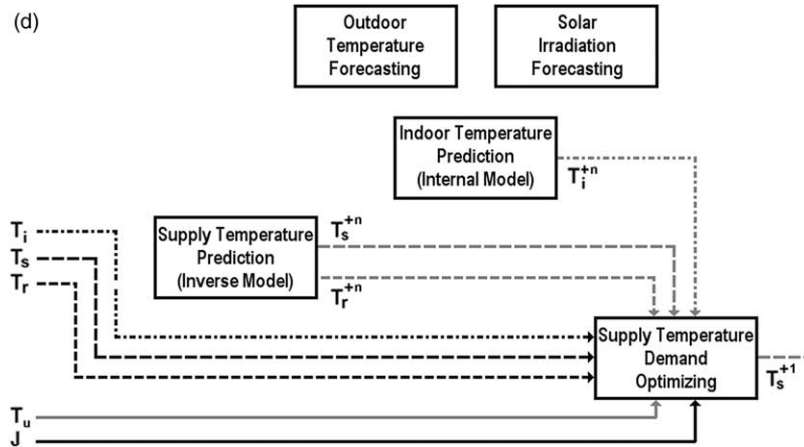


Fig. 2 (continued)

(i) Between two classes of ANN architectures that are well suited for the task of predicting the heating energy demand, namely the Time Delay Neural Network and the Feed Forward Back Propagation (FFBP). The FFBP model

(Kartalopoulos, 1996) was selected for all modules of the controller, since it showed a lower prediction error and a more stable error development in ANN training. (ii) The selection of the appropriate number of layers (input, hidden

Table 1

Hydronic ANN controller: modules, input and output parameters (The architecture of each ANN is also defined (Example: $i18\ h32\ h32\ o4 = 18$ input units followed by 32 hidden units followed by 32 hidden units followed by four output units))

G_s	$i18\ h32\ h32\ o4$	Solar irradiation forecasting ANN-module
Input	$N_h^{(0)}$	(Daily normalized) time value for the last time step
Input	$N_d^{(0)}$	(Yearly normalized) day number for the last time step
Input	$T_{amb}^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the ambient temperature
Input	$G_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the solar irradiance
Output	$G_s^{(+1,+2,+3,+4)}$	Solar irradiance for the next four time steps
T_{amb}	$i18\ h32\ h32\ o4$	Ambient temperature forecasting ANN-module
Input	$N_h^{(0)}$	(Daily normalized) time value for the last time step
Input	$N_d^{(0)}$	(Yearly normalized) day number for the last time step
Input	$T_{amb}^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the ambient temperature
Input	$G_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the solar irradiance
Output	$T_{amb}^{(+1,+2,+3,+4)}$	Ambient temperature for the next four time steps
T_s	$i52\ h32\ h32\ o12$	Supply temperature predicting ANN-module (inverse model)
Input	$T_{amb}^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the ambient temperature
Input	$G_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the solar irradiance
Input	$T_i^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the indoor temperature
Input	$T_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the supply temperature
Input	$T_r^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the return temperature
Input	$T_{amb}^{(+1,+2,+3,+4)}$	Ambient temperature for the next four time steps
Input	$G_s^{(+1,+2,+3,+4)}$	Solar irradiance for the next four time steps
Input	$T_u^{(+1,+2,+3,+4)}$	User set temperature for the next four time steps
Output	$T_s^{(+1,+2,+3,+4)}$	Supply temperature for the next four time steps
Output	$T_r^{(+1,+2,+3,+4)}$	Return temperature for the next four time steps
Output	$D_i^{(+1,+2,+3,+4)}$	Difference between the supply and the return temperature
T_i	$i56\ h32\ h32\ o4$	Indoor temperature predicting ANN-module (internal model)
Input	$T_{amb}^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the ambient temperature
Input	$G_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the solar irradiance
Input	$T_i^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the indoor temperature
Input	$T_s^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the supply temperature
Input	$T_r^{(0,-1,-2,\dots,-7)}$	Last and seven previous values of the return temperature
Input	$T_{amb}^{(+1,+2,+3,+4)}$	Ambient temperature for the next four time steps
Input	$G_s^{(+1,+2,+3,+4)}$	Solar irradiance for the next four time steps
Input	$T_s^{(+1,+2,+3,+4)}$	Supply temperature for the next four time steps
Input	$T_r^{(+1,+2,+3,+4)}$	Return temperature for the next four time steps
Output	$T_i^{(+1,+2,+3,+4)}$	Indoor temperature for the next four time steps

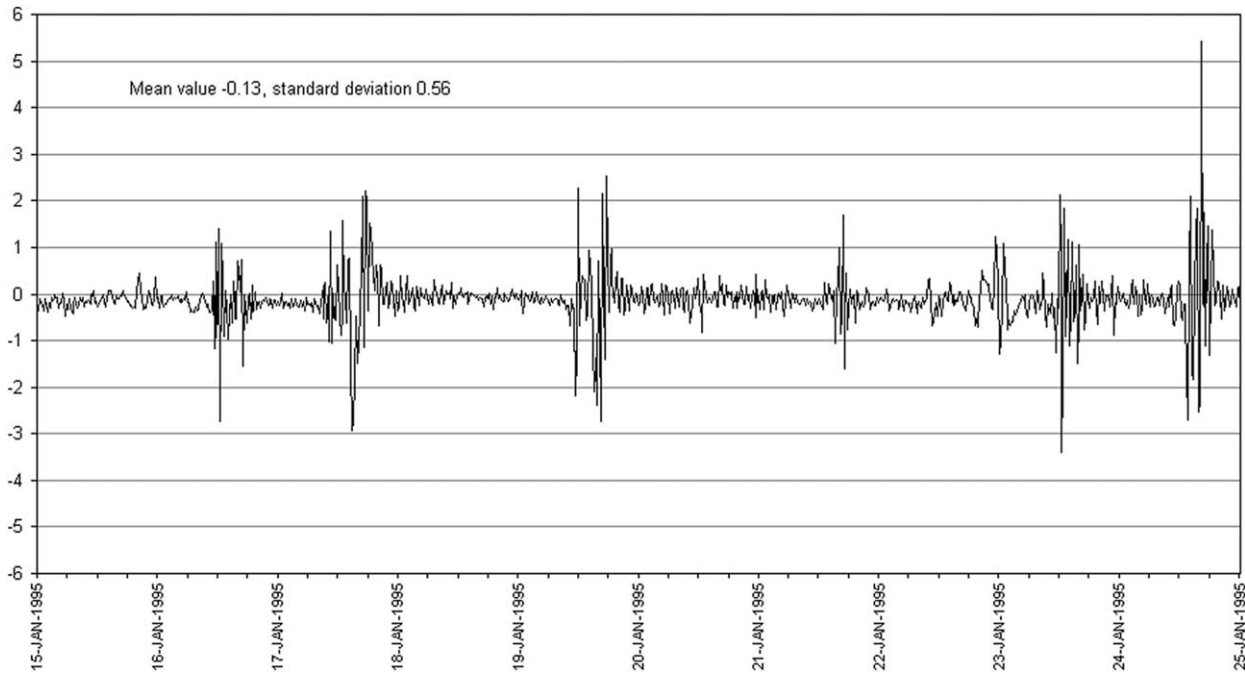


Fig. 3. Difference between 'real' water supply temperature and value calculated by the ANN.

and output) for each module and the error development when performing predictions for several steps ahead. The finally adopted modules, their inputs and outputs are shown in Table 1.

The data required for the off-line training of the controller were produced using the TRNSYS simulation code (Klein et al., 1994). This software allows the thermal simulation of buildings and of their heating, ventilation and air conditioning equipment. The simulation code was used in order to model the experimental solar house and its hydronic heating plant, belonging to the Institut für Solarenergieforschung GmbH, Hameln, Germany (Argiriou & Bellas-Velidis, 2000). The simulation results produced, using real weather data from the area of Hannover, Germany, were used for the training and validation of the produced ANN controller.

Fig. 3 shows the difference between the supply temperature of the heating plant as calculated by the ANN controller minus the 'real' (i.e. simulated) value. It can be seen that the ANN controller is able to accurately calculate the required supply temperature in general. Some points, however, show important discrepancies. These occur during daytime and in cases when the meteorological module cannot predict fast variations of solar irradiance, like in cases of clouds passing in front of the sun. However, the average temperature difference equals -0.13 ± 0.56 K.

3. Performance criteria

For the performance assessment of a water supply temperature controller of a hydronic heating plant, several

criteria should be taken into account like thermal comfort, operating costs and also environmental concerns (pollution due to energy consumption, etc.). In optimal control theory the above are combined in a so-called 'cost function' for which a minimum is sought (Bryson & Ho, 1981). For the purposes of the present work, this cost function is chosen as an expression of the trade-off between thermal comfort and energy consumption

$$J = \alpha J_d + J_e \quad (1)$$

with J_d , the discomfort cost function; J_e , the energy cost function; α is the weighting factor between energy and comfort.

The chosen indicators for thermal comfort are the widely accepted 'Predicted Mean Vote' (PMV) and the 'Predicted Percentage of Dissatisfied' (PPD) introduced by Fanger (1972). The PMV is an estimation of the average vote of a large group of persons subjected to a given thermal environment, if they are asked to rate it using a scale ranging from -3 to 3 (-3 if too cold, 0 if neutral and 3 if too hot). The PPD is an estimation of the percentage of occupants who would not be satisfied by the thermal environment.

The above indicators depend on six environmental parameters, namely the air temperature, mean radiant temperature, air velocity, relative humidity, specific metabolic activity and the clothing thermal resistance. In the discomfort cost, PPD is calculated with default values for non-simulated parameters (air velocity, relative humidity and metabolic activity). Furthermore, it is assumed that the occupants can adapt their clothing to the zone temperature. These indicators allow modelling a comfort range within

which the occupants are satisfied. With the selected parameter values, the comfort zone covers operative temperatures (i.e. a weighted sum of air and mean radiant temperature; this is closer to the comfort feeling than the air temperature alone (Athienitis, 1991)) between 21 and 24 °C. The PPD is also shifted down by 5% in order to give a value of 0, since according to its definition, the minimum value of PPD is 5% (Fanger, 1972). Thus, the discomfort cost is:

$$J_d = \int (\text{PPD} - 5\%) \quad (2)$$

The energy cost is considered to be proportional to the energy consumption of the boiler (Q_b):

$$J_e = \int \dot{Q}_b \quad (3)$$

This is simply the energy consumption, expressed in kilowatt-hour.

4. Experimental tests

The controller was experimentally tested at the passive solar office building of the Fondation Universitaire Luxembourgeoise, Arlon, Belgium. Two offices of 30-m² floor area each and the adjacent south facing sunspace were selected for these tests. The sunspace is 1 m deep and totally glazed. It is separated from the offices by a mass wall (25-cm thick heavy concrete) including 10 m² internal windows. The offices have also 2 m² external windows in the roof, which can be operated by the occupants. The heating system

includes a boiler, a three-way valve and a radiator. The control variable is the water supply temperature T_{ws} . The controlled variable is the operative zone temperature in the offices (T_{op}).

The ANN controller was compared to a conventional existing controller. The latter is a classical feed-forward controller (PID) based upon the ambient temperature, which adapts the supply temperature by means of a three-way valve according to a value calculated by the ‘heating curve’. The ANN controller was implemented in a non-intrusive way in order to allow an easy fallback solution if needed. For this reason ambient (external) temperature sensor of the conventional controller was removed and replaced by a software sensor representing the fictitious ambient temperature corresponding to the optimized supply temperature as calculated by the ANN controller. This fictitious temperature is calculated from a reverse use of the heating curve (Fig. 4). T_{ws} is the set point for the water supply temperature. The software sensor is implemented through a voltage-controlled resistor (a JFET transistor). The control voltage (which fixes the resistance value) is applied by a conventional AD/DA board installed on the personal computer.

The two controllers were not tested in parallel but in different time periods, since only one controller can be implemented to the hydronic system. Traditional heating control strategies include a feed-forward action on water supply temperature by the so-called ‘heating curve’ and a feedback action on water flow rate by a thermostatic valve. Two heating curves are used for ‘day’ (occupied building) and ‘night’. The heating curve gives the value of T_{ws} as

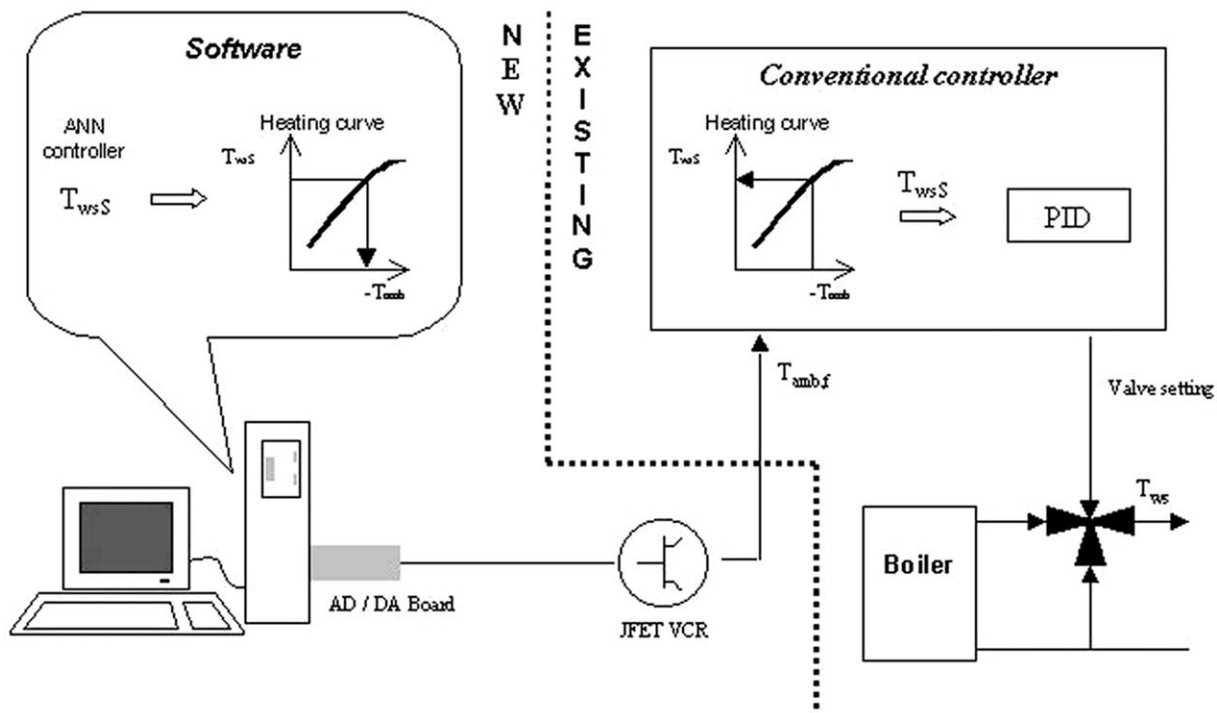


Fig. 4. Physical implementation of the ANN and conventional controllers.

a function of the ambient temperature, T_{amb} . The value of T_{ws} for a given T_{amb} is calculated using the static properties of the building. The desired temperature in the reference zone (15 °C during night time, 21 °C during daytime) should be maintained if the building was subjected to the given ambient temperature for a long period, without any solar radiation.

In common practice, the ‘day’ heating curve is slightly overestimated in order to allow a faster warm-up of the building, while the ‘night’ heating curve can be slightly underestimated in order to take into account the dynamic behaviour (the initial building temperature is always higher than the desired value).

Thermostatic valves are traditionally combined with heating curves. These valves can reduce the flow rate in the radiators in order to prevent overheating. The role of the valves is thus very important since neither the internal gains nor the solar radiation are taken into account by the heating curve. The thermostatic valves have a proportional band of 2 °C and a hysteresis of 0.5 °C, which is representative of commercially available models. The valve temperature depends on the zone temperature but also on the water supply and radiator temperatures. This problem is taken into account by the model used in the simulations (IEA, 1988). The valves are supposed to be maintained at the desired ‘Day’ set point all the time. Switching between ‘Day’ and ‘Night’ heating curves is decided according to a fixed schedule throughout the heating season.

A summary of the climatic conditions, energy consumption and comfort during the testing periods the conventional and the ANN controller is shown in Table 2. It can be seen that although the weather conditions were in average much colder when the ANN controller was tested, the energy consumption is practically identical to the one when the conventional controller was used, with much better comfort results. As shown also in Table 2, the average measured heating power over a two-week period using the conventional controller was found to be 0.422 kW. The use of the ANN controller over a similar (cold and sunny) two-week period required 0.345 kW. Therefore the ANN controller achieved in average about 18% energy savings.

Fig. 5 shows two-day typical profiles of a series of variables during the operation of the ANN controller. These variables are: operative temperature in the two offices (T_{op}), water supply temperature (T_{ws}), water return temperature (T_{wr}), ambient temperature (T_{amb}) and the solar irradiance on the south vertical plane (G_{south}). Grey rectangles represent the comfort temperature range (21–24 °C) during the occupancy period of the building (08:00–18:00). The discomfort cost is zero in this temperature range. The lower light grey rectangles indicate the zone where the comfort is still very low (i.e. 0.5 °C below the lower limit or above the upper limit).

From these graphs it can be seen that the operative temperature is within the comfort range (darker grey rectangle) during the occupancy period of the building except at the very beginning of this period, where the temperature reached the zone of very low discomfort cost (light grey area). The second day shows that the ANN controller is able to react to sunshine to prevent overheating.

5. Simulation results

The performance of the ANN controller over a complete heating season and its comparison with a conventional controller was performed using the detailed thermal simulation code TRNSYS (Klein et al., 1994), combined with the MATLAB software (The Mathworks, 1999). The simulation environment, shown in Fig. 6, includes the following components:

- Building model (TRNSYS TYPE 56 module): This model has been validated by the IEA (Lomas et al., 1994).
- Radiator and thermostatic valve (TRNSYS Types 182 and 183): these are based on the IEA Annex 10 models (IEA, 1988).
- Boiler and three-way valve: the boiler is supposed to have a constant set point (70 °C). This is the maximum water supply temperature (T_{ws}) value. The three-way valve can adjust the water supply temperature between

Table 2
Comparison between the conventional and ANN controller

	Conventional		ANN	
	Global summary	Similar periods	Global summary	Similar periods
T_{amb} (°C) (average)	5.4	−4.1	2.8	−3.6
G_h (W m ^{−2}) (average)	86	56	68	68
J_d (%) (max)	14.3	1.6	2.5	2.5
J_d (%) (average)	0.30	0.05	0.04	0.04
Heating power (kW)	0.338	0.422	0.339	0.345

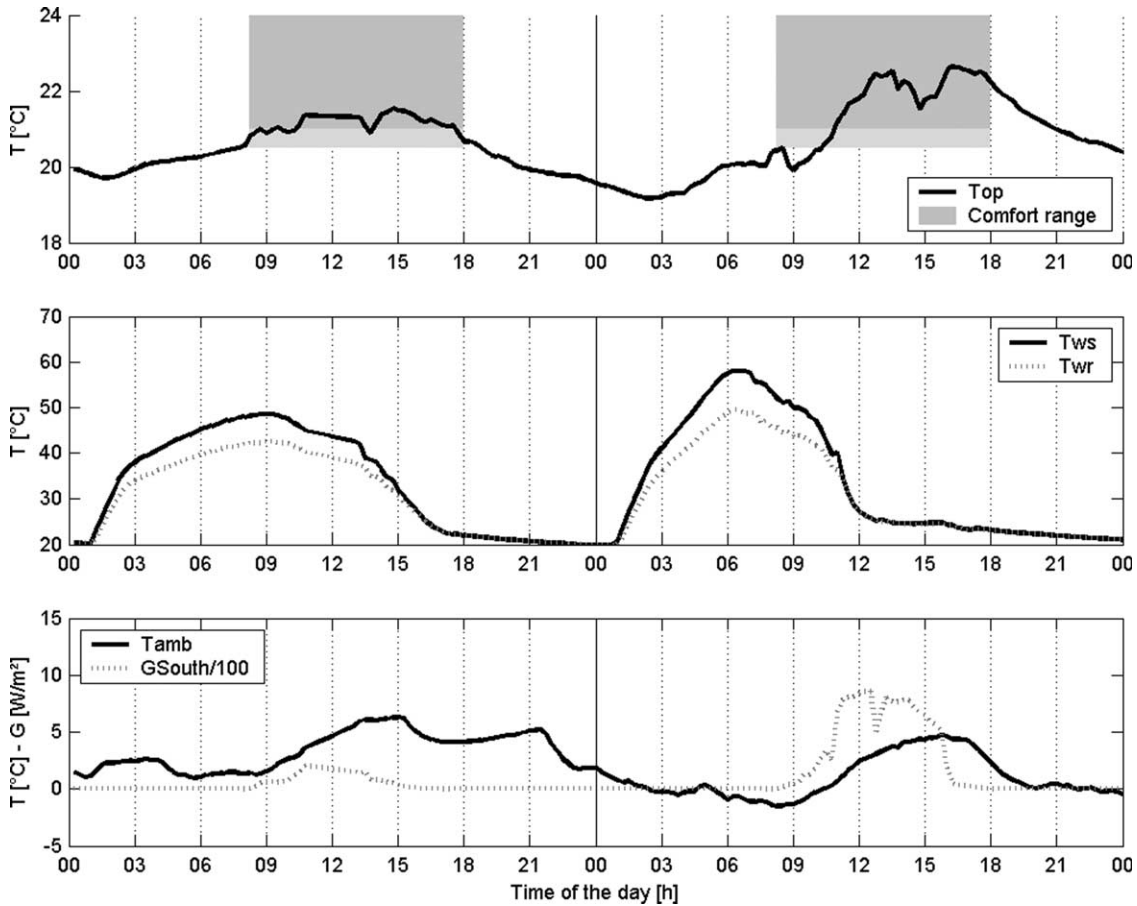


Fig. 5. Profiles of T_{amb} , T_{ws} , T_{wr} , Q_r , T_{amb} and G_{south} . Gray rectangles represent the comfort temperature range (21–24 °C) during the occupancy period (08:00–18:00). Discomfort cost is zero in this temperature range.

a lower bound defined by the return water temperature (T_{wr}), and an upper bound is defined by the maximum boiler power: if all available power is used, the boiler cannot reach its set point and the maximum supply temperature is reduced. These constraints are taken into account by simple equations. The circulating pump

is assumed to run continuously, as it is common in office-type buildings.

- User behaviour and natural ventilation (TRNSYS Type 201): The building has windows that can be operated by the occupants. The user behaviour concerning windows opening is modelled as follows:

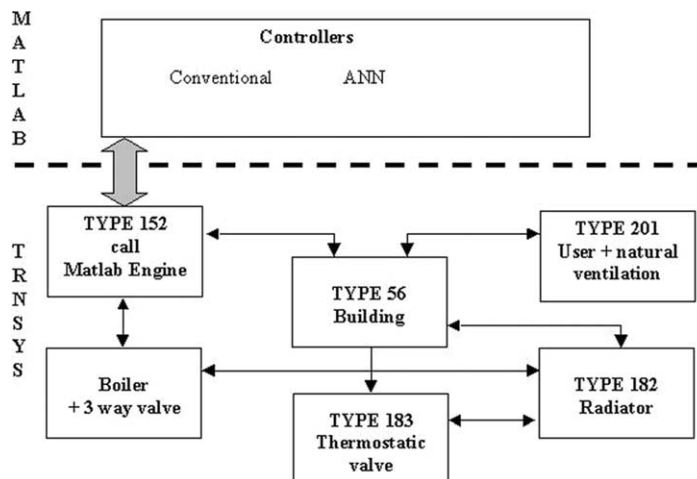


Fig. 6. Flow chart of the TRNSYS simulation environment.

Table 3
Heating start time for different schedules

Heating schedule No.	Start time (Sunday)	Start time (Monday)	Start time (Tue–Fri)
5	–	0	3
6	21	0	2
7	16	0	1

- If the temperature is higher than the upper comfort limit, occupants open the window.
- If the temperature is below the lower comfort limit, they close the window.
- If the temperature is within the comfort range, the window is left in its current position.
- The windows are closed when the occupants leave the building in the afternoon.
- Controller call (TRNSYS TYPE 152): The controllers are implemented in MATLAB. For the controllers for which an executable program is available, the file data transfer and the call to executable routine are also implemented in MATLAB. The TYPE 152 is not a standard TRNSYS routine but was developed specifically for the needs of this research.

The simulation used real weather data from Uccle (Brussels, Belgium) for the period from September 28, 1985 to April 25, 1986. Real data were preferred instead of a Typical Reference Year, in order to allow a full testing of the forecasting features of the ANN controller.

The occupancy profile was selected in order to allow the study of the heating start-up period problems. The building is supposed to be occupied from 08:00 to 18:00 from Monday to Friday. No occupants are present during the weekend. The night set point temperature is 15 °C. The day set point was determined by the comfort considerations described in Section 3 of this paper.

The heating system is controlled using a fixed schedule; heating starts early enough so that the desired temperature is achieved upon the arrival of the occupants. The heating schedule has a strong influence on the comfort and energy performance. If the heating system starts too late, the discomfort will be high during the beginning of the occupancy period. On the other hand, if the heating starts too early, energy is wasted and the overheating risk during the afternoon is more important since the building structure will be warmer. In order to investigate this influence, three heating schedules were tested. The start time of the heating system for these schedules is shown in Table 3. The heating system stops at 18:00 in all cases.

In Fig. 7 the average PMV values over the heating season are shown. The PMV indicates that both controllers achieve thermal comfort conditions; the conventional controller gives values slightly positive values while the ANN controller gives slightly negative ones.

Fig. 8 shows the variation of the energy cost against the discomfort cost for the two controllers and the various heating schedules. The conventional controller curves have several points for each schedule, obtained by several thermostatic valve settings, while with the ANN controller

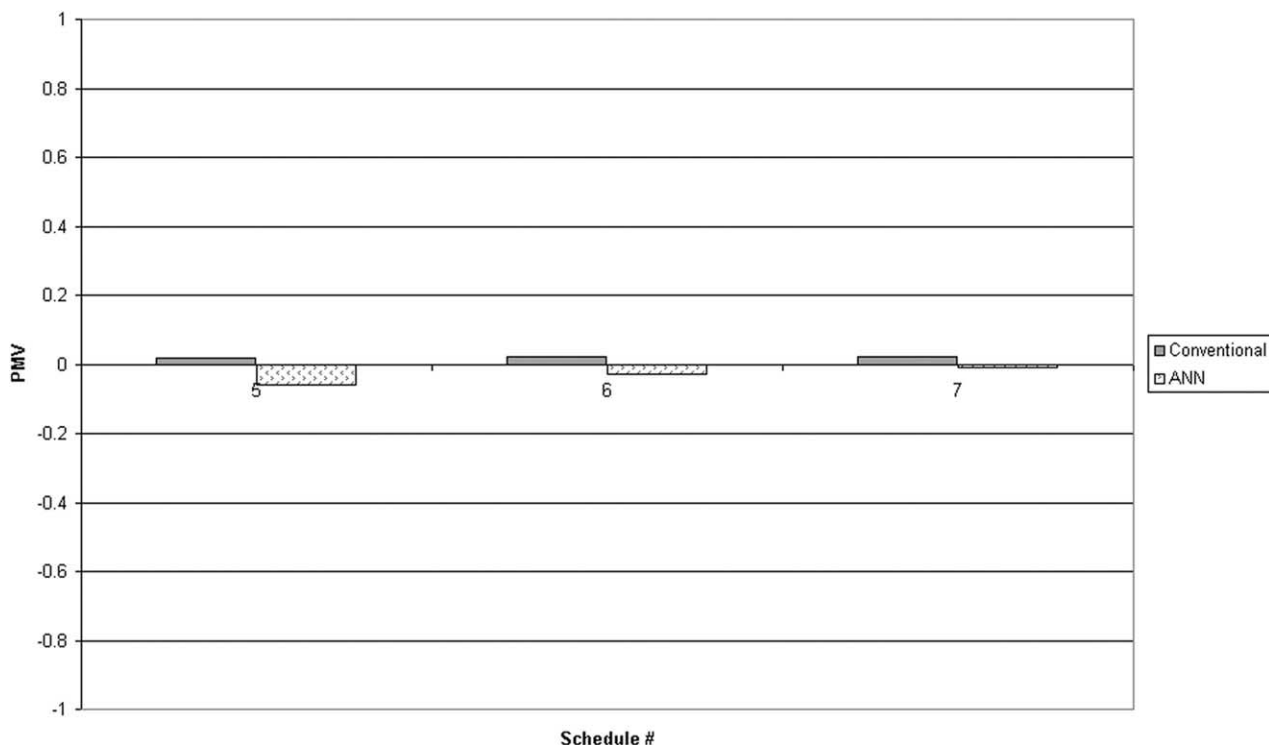


Fig. 7. Predicted Mean Vote (annual averages) using the ANN controller, as a function of the heating schedule.

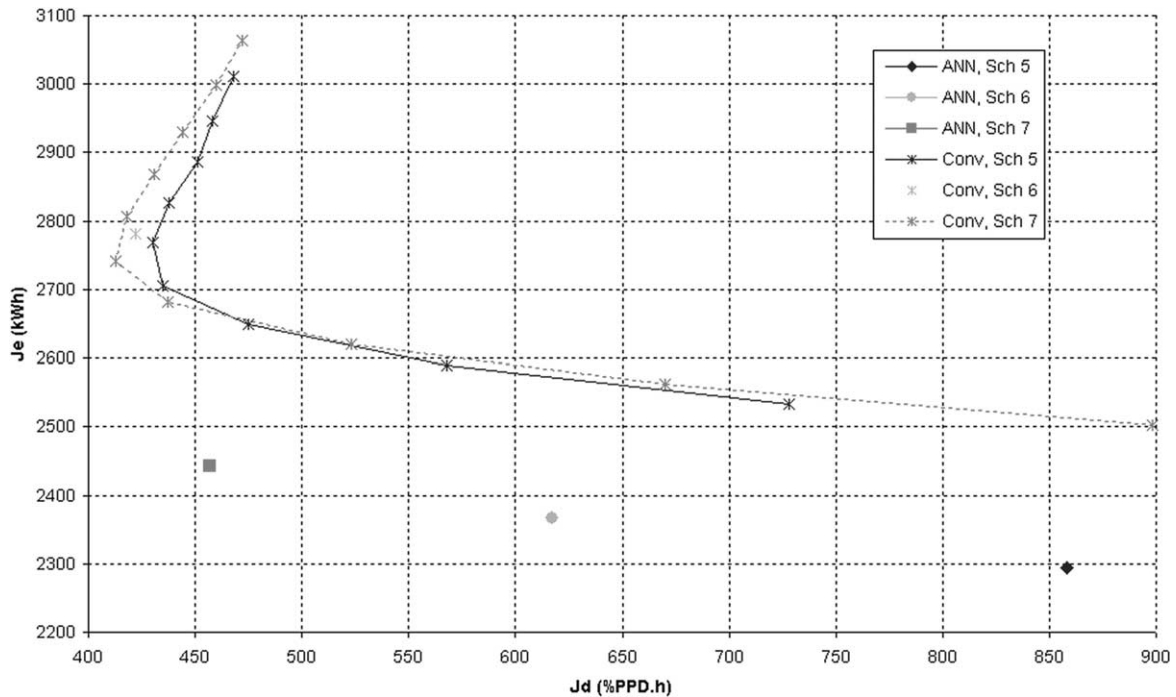


Fig. 8. Variation of the energy cost as a function for the discomfort cost for the conventional and ANN controller.

the thermostatic valve is constantly open. It can be seen that for a given discomfort cost value (i.e. identical comfort conditions in the building) the ANN controller presents always a lower energy cost compared to the conventional controller. The relatively high discomfort cost values occurring when the ANN controller is used with heating schedules 5 and 6, are due to the fact that this controller has no ‘boost’ period implemented in order to cope with ‘cold mornings’ occurring on Mondays. This problem is not observed with heating schedule 7, where a longer

pre-heating time is available in order to reach the comfort temperature before the building occupants arrive.

Fig. 9 shows the annual heating energy savings in percent between the conventional and ANN controller. This ranges between 13 and 17%, depending on the heating schedule type. These figures are consistent with the 18% of energy savings achieved experimentally (Section 4). The relative performance of the two controllers is better illustrated when focusing to specific time periods. For this purpose, two periods were chosen: a cold week and a sunny mid-season

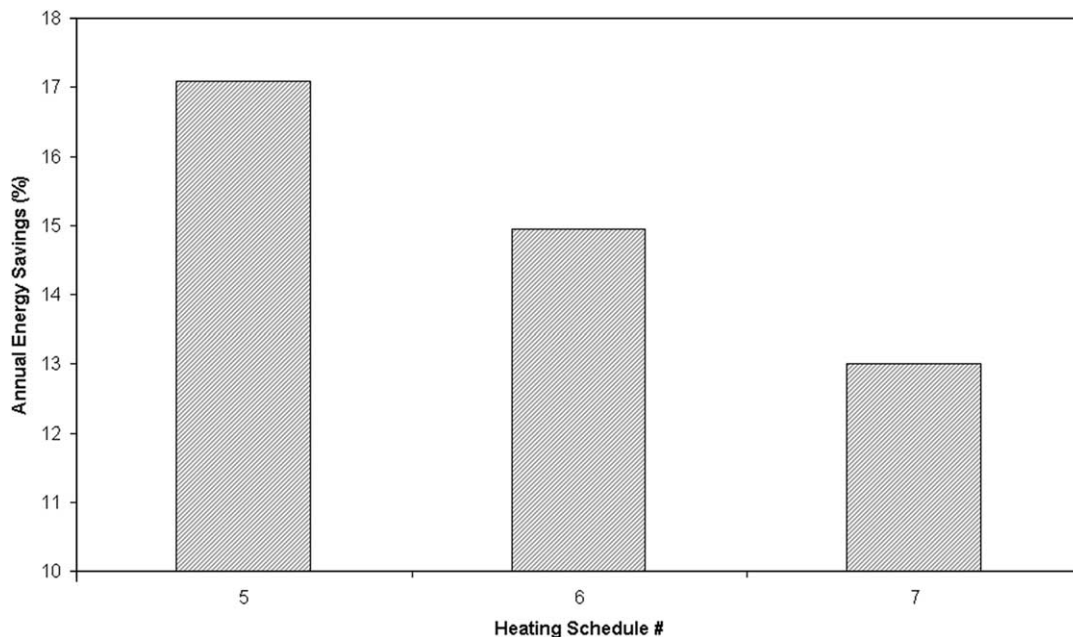


Fig. 9. Estimated percentage of annual energy savings due to the ANN controller. Comparison is made against a conventional controller.

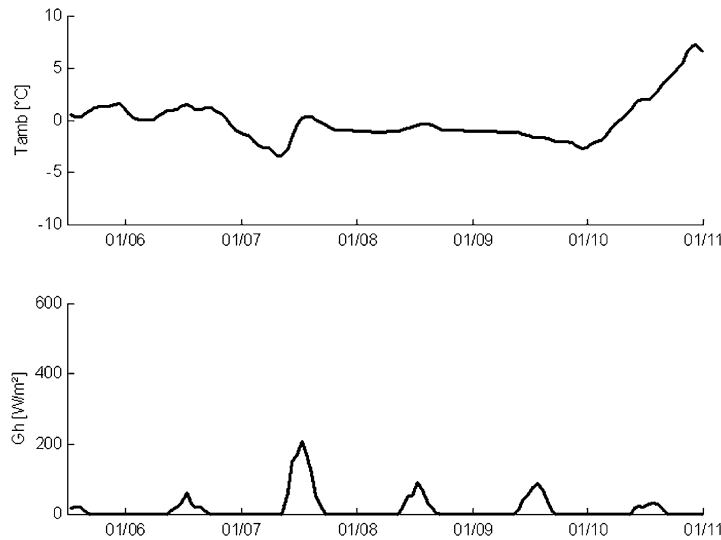


Fig. 10. 'Cold week' simulation period. Ambient temperature (top graph) and global horizontal solar irradiance (bottom graph).

week. Figs. 10 and 11 show the ambient temperature and global horizontal irradiance for these two periods.

Figs. 12 and 13 show the behaviour of the conventional and of the ANN controller during the cold week, for different heating schedules and different thermostatic valve settings. The comparison of these figures shows that the temperature during the night is higher when the conventional controller is used. This is due to the fact that the conventional controller uses a heating curve designed to maintain the night set point constant (15 °C) in steady-state conditions. The building is always coming from a higher temperature and the heating curve overestimates the required supply temperature. The thermostatic valves do not have any effect to correct this overestimation at night since they are left on the 'Day' set point (21 °C). Also the proportional band of the thermostatic valves makes that

the heating power is decreased when the zone temperature reaches the set point, but the heating power is not zeroed. The ANN controller has a slower response and this may lead to high discomfort on some mornings, as on the first day of the plot. This implies the use of rather conservative heating schedules. On the other hand, the set point is well maintained and the heating power is zeroed when necessary, contributing to the energy savings.

The behaviour of the controllers during the sunny mid-season period is shown in Figs. 14 and 15. It can be noted that during this period, the building is significantly warmer with the conventional than with the ANN controller. This is again due to the use of fixed set points for thermostatic valves combined with a steady-state heating curve. The use of a fixed heating schedule leads to a pre-heating of the building, which is also unnecessary during this rather

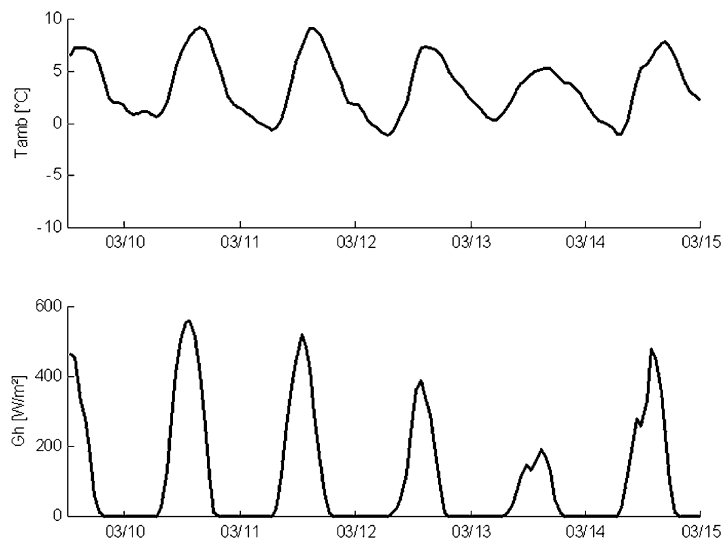


Fig. 11. 'Sunny mid-season' simulation period. Ambient temperature (top graph) and global horizontal solar irradiance (bottom graph).

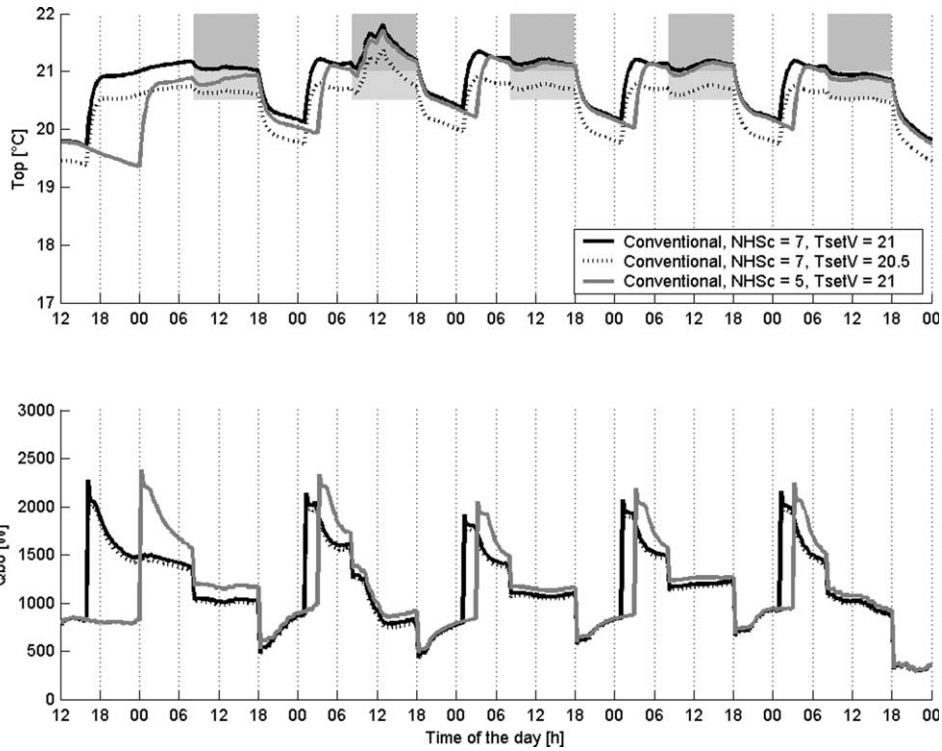


Fig. 12. Performance of the conventional controller during the ‘cold week’ (top graph: operative temperature; bottom graph: heating power).

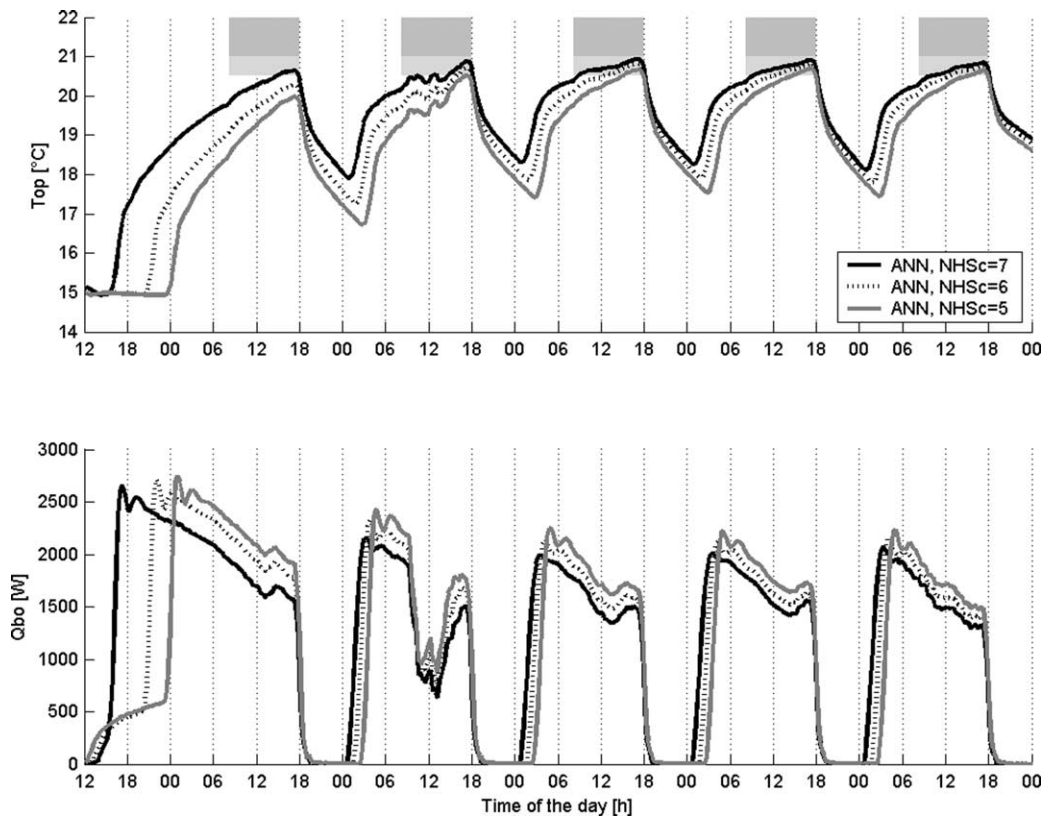


Fig. 13. Performance of the ANN controller during the ‘cold week’ (top graph: operative temperature; bottom graph: heating power).

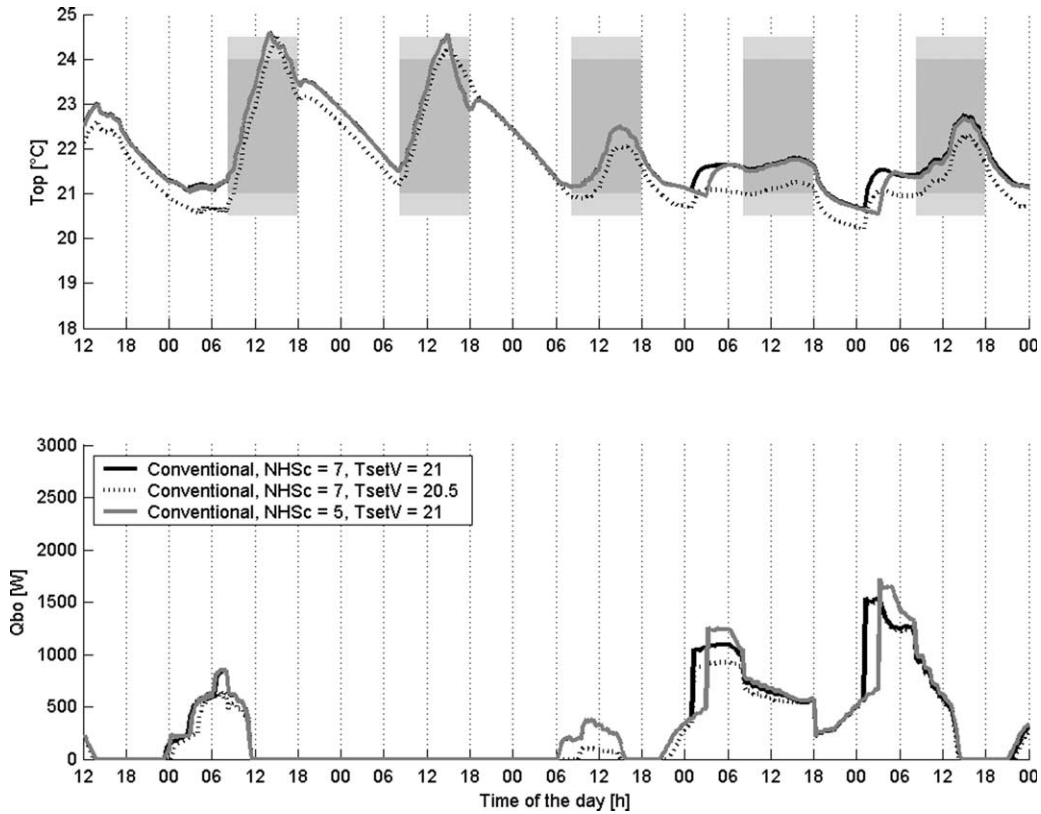


Fig. 14. Performance of the conventional controller during the ‘sunny mid-season week’ (top graph: operative temperature; bottom graph: heating power).

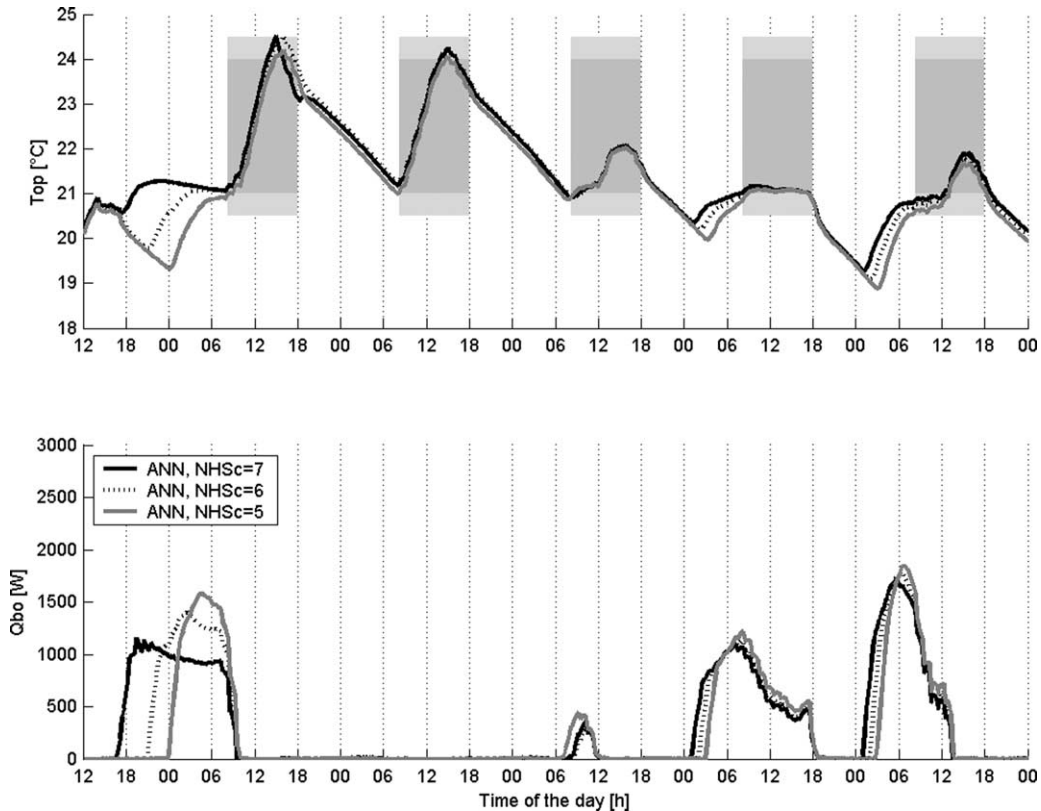


Fig. 15. Performance of the ANN controller during the ‘sunny mid-season week’ (top graph: operative temperature; bottom graph: heating power).

warm week. Energy is wasted and the overheating risk during the afternoon is more important. These problems are avoided with the ANN controller.

The problem posed by such a controller is that it requires training in each new site. In the frame of this work, the training was performed off-line using existing data sets both for the weather parameters and also for the thermal performance of the heating plant and building. For commercial applications the on-line adaptation possibility offered by the neural networks should be used. In order to investigate this possibility an additional module was developed and tested off-line in the numerical simulation environment. The results demonstrated that the controller trained with this module showed the same behaviour as the modules trained with the SNNS.

6. Conclusions

This paper demonstrated the potential of an ANN controller for the control of hydronic heating systems towards energy savings while maintaining thermal comfort. The use of ANNs provides the controller with forecasting capabilities of both weather parameters and indoor conditions. The operation of the controller has been tested both experimentally, on a real-scale office building and via numerical simulation. The implementation of the ANN controller revealed that the absence of 'boost' module able to cope with step changes in the set point temperature (i.e. from 15 to 21 °C) in the mornings resulted often to discomfort. Implementing an additional module trained in such a way to enable the fast warm-up of the building can solve this problem. For the needs of this study adopting long pre-heating schedules in the beginning of the week faced the problem.

Experimental testing showed that the ANN controller leads to 18% of energy savings over the test period with respect to the conventional one. Simulations showed that energy savings over the heating season range from 13 to 17%, depending on the heating schedule used. Therefore, an expected percentage of energy savings under North European conditions of about 15% can be claimed.

Acknowledgements

This work has been partly funded by the European Commission, Directorate General XII (Contract JOE3-CT97-0076).

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