NEUROBAT, A PREDICTIVE AND ADAPTIVE HEATING CONTROL SYSTEM USING ARTIFICIAL NEURAL NETWORKS

NICOLAS MOREL [A], MANUEL BAUER [B], MARIO EL-KHOURY [C] AND JENS KRAUSS [C]

LESO-PB/EPFL, LAUSANNE, SWITZERLAND; [B] ESTIA LTD, PSE-B/EPFL, LAUSANNE, SWITZERLAND; [C] CSEM, NEUCHÂTEL, SWITZERLAND

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The paper describes a predictive and adaptive heating controller, using artificial neural networks to allow the adaptation of the control model to the real conditions (climate, building characteristics, user's behaviour). The controller algorithm has been developed and tested as a collaborative project between the CSEM (Centre Suisse d'Electronique et de Microtechnique, Neuchâtel, Switzerland, project leader), and the LESO-PB (Solar Energy and Building Physics Laboratory, EPFL, Lausanne, Switzerland). A significant support has been provided by leading Swiss industries in control systems. The project itself has been funded by the Swiss Federal Office of Energy (SFOE).

The project has allowed the development of an original algorithm, especially suited for water heating systems, and its testing both by simulation and by experimentation on an inhabited building. The experimentation has been done using a PC software implementation. A second phase of the project, currently going on, aims at building a commercial system based on the NEUROBAT algorithm.

Keywords: Heating Equipment, Self Commissioning, Adaptive Controller, Predictive Controller, Artificial Neural Networks (ANN), Fuzzy Logic.

1. INTRODUCTION

The control strategy of existing water heating systems is usually based on a set of predefined heating curves which determine the nominal flow temperature of the heating fluid as a function of the external temperature. This open-loop control concept leads to poor energy management, reduced thermal comfort, or requires a considerable commissioning effort during installation and maintenance in order to provide a reasonable energy management and thermal comfort. Thermostatic valves located on individual radiators allow to take into account the inside air temperature, but only partially and imperfectly. The drawbacks of such systems is not compensated by a continuous adaptation of the control parameters.

During the last years, significant advances have been done for the HVAC control systems. For instance, continuous adaptation of control parameters, optimal start-stop algorithms, or inclusion of passive solar or other free heat gains in the control algorithm, have allowed to make the heating control systems better. Nevertheless, even the best systems do not yet operate in an optimum way.

In order to ensure an intelligent management of the free heat gains (solar and internal gains), a predictive and adaptive heating control system has been developed and tested by CSEM (Centre Suisse d'Electronique et de Microtechnique) and LESO-PB (Laboratoire d'Energie Solaire et de Physique du Bâtiment, EPFL). Like several commercial systems, the new controller is interfaced to four temperature sensors located at the departure of the heating fluid, its return, in a reference room, and outside the building. The former two measurements allow to estimate the heat transfer occurring between the fluid and the building. The new controller is also designed to take advantage of a solar sensor to anticipate the solar gains and reduce energy consumption.

The choice of a predictive control strategy, combined with the non-linear modelling of the building and user's behaviour, and with the weather prediction, allows the NEUROBAT controller to achieve energy savings while ensuring a good thermal comfort. Moreover, the commissioning time of the new controller is considerably reduced, thanks to the use of self-learning neural algorithms.

The NEUROBAT concept has been checked both by simulation and by experimental tests on a real inhabited building. The simulations are based on a complex nodal network building model, adjusted and validated to the test building rooms chosen for the NEUROBAT project, and implemented using the Matlab environment. Based on real data collected during the test phases, for the climate, the building and the user's behaviour, the performances of the NEUROBAT controller have been simulated and optimised off-line. In order to complete the comparative tests, the commercial heating control system has been modelled on the Matlab platform.

The experimental tests have been done on two identical office rooms on the South facade of the LESO building. To compare the performances of the NEUROBAT controller with an advanced commercial HVAC controller, the office rooms have been equipped with two independent hot water heating circuits. One of the room is controlled by the NEUROBAT controller, and the other one by the commercial HVAC controller. The experiments have been completed during the heating seasons 1996/1997 and 1997/1998.

The NEUROBAT project, phase 1 ([1], [2], [3]) has been funded by the Swiss Federal Office of Energy (SFOE). The project objectives and results have been supervised during the project duration (February 1996 to April 1998) by a steering committee, including representatives of the SFOE and the main Swiss HVAC control system suppliers.

Considering the good results obtained by the project, a second phase (NEUROBAT phase 2) has been started at the end of 1998, in close collaboration with one important Swiss manufacturer of HVAC control system.

The global objectives for the NEUROBAT heating controller have been defined as below:

- ensuring an optimal comfort of the user with the help of an intelligent management of the solar and internal gains on a predefined prediction time horizon, by means of an optimal control algorithm;
- reducing the energy consumption;
- minimising the commissioning and maintenance effort (self-commissioning control strategy, continuous adaptation of the control parameters, efficient optimal start/stop control);
- adapting to the user's occupation and behaviour.

2. NEUROBAT CONTROLLER DESCRIPTION

2.1 Controller concept

The concept of the NEUROBAT controller includes the following features:

- The prediction of the climate data, such as the solar radiation and the external temperature, enables the anticipation of the solar gains and heat losses towards outside and optimises the user comfort on a long-term base ([4], [5], [6]).
- Artificial neural networks (ANN) are particularly well adapted to deal with non-linear systems, such as the thermal behaviour of a building, due to the changing solar gains (blind position adjusted by the user), the convective heat exchange, the window opening, etc ([7], [8]). In addition, their self-learning features provide a powerful tool to design a self-commissioning heating control system, simplifying the installation and maintenance procedures.
- With the help of the linguistic description of fuzzy parameters, the user comfort expression can be integrated into the control loop of the heating system. For the tests, either by simulation or by measurement on a inhabited office room, a 20 °C temperature setpoint has been used.
- In comparison to the widespread temperature management of conventional building control systems, the NEUROBAT controller allows a predictive energy optimisation on a fixed time horizon [9]. In our case, a 6-hour time horizon is used. Each 15 minutes, the optimal heating power is recalculated, taking into account this time horizon.
- To be able to interface the NEUROBAT control algorithm with conventional actuators (mixing valve), a cascaded control loop has been implemented: the outer control loop optimises the heating power; the inner control loop controls the inlet temperature of the heating fluid, the heating fluid flow temperature being calculated from the optimal heating power and the measured return temperature of the heating fluid.

The complete concept is shown in Figure 1 below.

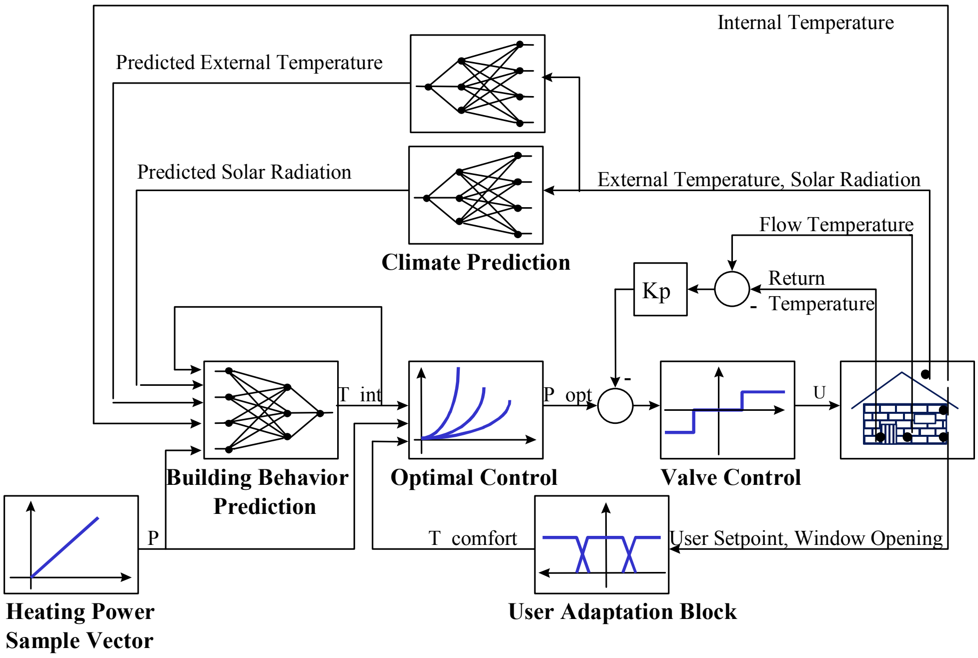

FIGURE 1: NEUROBAT controller concept

2.2 Solar radiation prediction model

For the prediction of the horizontal global radiation [W/m^2] on a 6 hour time horizon, an ANN trained with data from the Swiss Meteorological Institute (ISM) has been used. Several prediction models have been compared. The "reference models" are very simple and are used as a performance reference for the other prediction models. The linear models (AR and ARX), applied in many other domains for the prediction of time series, are designed, like the ANN models, with adaptive features. The output of the stochastic prediction models is probability-based and transformed into deterministic values for the comparison. The various prediction models are detailed below.

2.2.1 Reference models (REF)

The reference model REF1 uses the current measurement of the horizontal global solar radiation as the prediction value for the six following hours; the reference model REF2 takes the atmospheric transmittence, i.e. the ratio between the current measurement of the horizontal global radiation and the extraterrestrial value of the horizontal global radiation [10], as the prediction value for the six following hours. During the night, the atmospheric transmittence is not defined and therefore the average value over the last hours of the previous day is considered as predicted value.

2.2.2 Linear models (AR/ARX)

The auto-regressive AR and ARX prediction models are linear adaptive models, whose parameters are estimated with the least-square method and whose equation is given by the following expression:

$$y(k) = \sum_{i=1}^{m} a_i \cdot y(k-i) + \sum_{i=1}^{m} \sum_{j=0}^{o_j} b_{ji} \cdot u_j(k-i)$$

where y is the output variable and u the input variable, a_i and b_{ji} the model parameters, and m and o_j the model order.

The AR1 model corresponds to an auto-regressive model of order 2 and uses the horizontal global solar radiation of time step k and k-1 as input. For the prediction up to six hours ahead, the estimated values of the previous time steps are used as inputs of the model. The ARX1 model uses in addition to the AR1 model the horizontal global solar radiation of the time step 24 hours ago, taking the periodic characteristic of the meteo into account. The ARX2 model is similar to the ARX1 model with the difference to take the relative horizontal global solar radiation (i.e. the atmospheric transmittence) as input.

2.2.3 Stochastic models (STO)

Stochastic model for the weather prediction (solar radiation and outside air temperature) has been already used in a predictive heating controller elaborated and tested at LESO [5]. The relevant parameters (solar radiation and outside air temperature) are discretised into classes, and a Markov matrix is assigned to the transition between the classes, for different day types (4 types are considered here). In our case, the atmospheric transmittance is discretised into 10 classes, thus leading to 10 x 10 Markov probability transition matrices.

In order to be able to compare the probability generated by the stochastic model with the reference, the linear and the neural network modes, two approaches have been chosen: the model STO1 generates a future transmittance by selecting the most probable value, while the model STO2 calculates the future transmittance by an average, using the transition probabilities as weighting factors.

2.2.4 Artificial neural networks models (ANN)

A simple feed-forward network structure with one hidden layer and all the neurones completely inter-connected has been chosen. The Levenberg-Marquart training algorithm [11] has been used for learning the ANN weights, using measured weather data. Several models with different inputs are applied for the horizontal global solar radiation; additional inputs include the maximum external temperature variation range during the last 6 or 24 hours (which gives an indication of the degree of cloudiness), and a time reference (1 for the day, 0 for the night, which allows to take into account night conditions cleanly). In the table I below, only the chosen model is given.

2.2.5 Model comparison

All the models have been compared by calculating the difference of the predicted solar radiation 1, 2, 3, 4, 5 or 6 hours ahead [W/m^2] and the real solar radiation at the same time ahead, using measured data not used for the learning of the model. Weather data measured in Lausanne has been used for the comparison (model training with winter 1982 data and model evaluation with winter 1983 data). The Table I below gives the standard deviation of the prediction error, for prediction times between 1 and 6 hours.

TABLE I: Standard deviation of the prediction error concerning the model of the global solar radiation on a horizontal surface, for time horizons from 1 to 6 hours, in [W/m^2]

	1 hour	2 hours	3 hours	4 hours	5 hours	6 hours
REF1	66	114	149	168	171	161
REF2	43	68	88	103	109	110
AR1	50	84	109	123	127	124
ARX1	46	73	87	93	94	93
ARX2	47	64	77	86	91	93
STO1	48	70	89	104	111	115
STO2	43	62	77	89	96	100
ANN	43	58	71	78	83	83

From the table, it appears clearly that the ANN models provide the best prediction for the 6 hours time horizon.

2.3 External temperature prediction model

As the second important disturbance source of the internal climate in a building, the external air temperature has been the subject of a similar comparison work. The following models have been evaluated, for the prediction 1, 2, 3, 4, 5 and 6 hours ahead:

- a reference model (REF1) considering the current measurement of the external temperature as the prediction value for the following six hours;
- two auto-regressive models (ARX1 and ARX2);
- two artificial neural network models (ANN1 and ANN2).

The investigation has been done with less detail than for the solar radiation: indeed, the impact of the instantaneous variations of the outside air temperature is less important, especially for well insulated and heavy buildings, than the average value during the prediction horizon.

The Table II below gives the standard deviation of the prediction error, for prediction times between 1 and 6 hours. Only the ANN finally chosen has been reported in the table.

TABLE II: Standard deviation of the prediction error concerning the outside temperature model, for time horizons from 1 to 6 hours, in [°C]

	1 hour	2 hours	3 hours	4 hours	5 hours	6 hours
REF1	0.50	0.82	1.10	1.34	1.55	1.73
ARX1	0.45	0.69	0.89	1.06	1.21	1.35
ARX2	0.44	0.67	0.85	1.02	1.19	1.35
ANN	0.45	0.69	0.92	1.07	1.18	1.31

In that case also, the artificial neural network model gives a better prediction, at least for a 5 or 6 hours ahead prediction, although not noticeably. Taking into account the better results given by the ANN models for the other predictors (solar radiation and building temperature), an ANN model has also been chosen for the outside temperature predictor, in order to have a similar structure for all the predictive building blocks of the controller.

2.4 Building model

Rather than using a physical model (based on thermo-physical properties and "first principles"), the NEUROBAT controller uses a behavioural model, based on an artificial neural network. The goal of the model is the prediction of the future value of inside temperature (only the inside air temperature is considered), based on the previous and current values for the inside temperature and the heat gains (solar gains, internal gains, heating equipment gains).

2.4.1 Model study on experimental data

Different variants of the ANN model were tested with experimental data, considering different inputs of the ANN. Besides the "reference" dummy prediction, given by the relation T(k) = T(k-1), the table III below gives the most performant variants, including both an ANN and an auto-regressive linear models (ARX). The time step considered is one hour; the ANN output is the difference between future temperature T(k) and current temperature T(k-1). Several other variants, with different inputs, have been also checked (see [1] or [3]).

In the Table III below, the global radiation on the window surface (Gv) is used. It is derived by a usual transposition method (see for example [10]) from the global radiation on a horizontal surface (Gh), which is the measured and predicted physical value.

TABLE III: Inputs used for the chosen ANN, ARX and reference [Ti(k) = Ti(k-1)] models. Ph = heating power, Ti = inside temperature, Te = outside temperature, Te = average outside temperature during the last 24 hours, Gv = global radiation on the window surface. For all the variables, the value X(k) is the hourly average value on the interval [k-1,k], except for Ti(k) which is the instantaneous value at time k.

	Pheating inputs	Inside air temperature inputs	Outside air temperature inputs	Solar radiation inputs
ANN	Ph(k)	Ti(k-1), Ti(k-2)	Te(k)	Gv(k), Gv(k-1)
ARX	Ph(k), Ph(k-1), Ph(k-2)	Ti(k-1), Ti(k-2), Ti(k-3)	Te(k), Te(k-1), Te(k-2)	Gv(k), Gv(k-1), Gv(k-2)
Reference		Ti(k-1)		

The initialisation of the ANN has been done randomly; the models have been trained over the data measured on the room 03 of the LESO building (see section 4), for the period February 14 to April 4, 1997, and the model has been tested using the period April 14 to May 1, 1997. The Table IV gives the standard error for the predictions at 1, 2, 3, 4, 5 and 6 hours ahead.

TABLE IV: Performance of building prediction model (standard errors in [°C])

	1 hour	2 hours	3 hours	4 hours	5 hours	6 hours
ANN	0.096	0.170	0.243	0.311	0.387	0.465
ARX	0.157	0.256	0.352	0.436	0.511	0.578
Reference	0.164	0.309	0.443	0.565	0.675	0.772

The most performant models do not use the current outside temperature, only the average value over the last 24 hours: this latter variable is enough to describe the building dynamics, even when the data include several window openings (the heat flow resulting from the air exchange between inside and outside depends directly on the instantaneous outside temperature).

The ARX model is not so good as the ANN model. This can be explained by the rather noisy input data, which includes several non-linearities and makes a linear model not very adequate.

The Figure 2 below shows the prediction at 6 hours for each model.

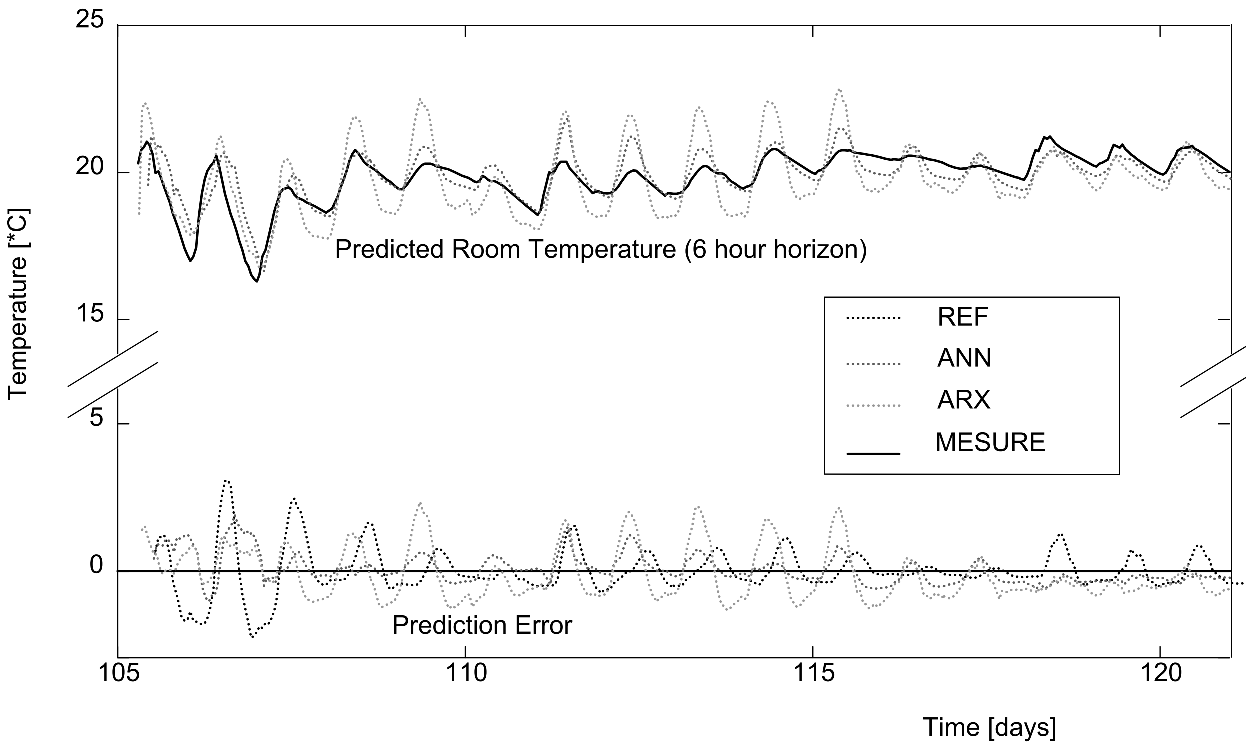

FIGURE 2: 6-hour prediction for ANN, ARX and Reference models. The results of the reference model, not shown directly in the figure, correspond to a delay of 6 hours of the measurement

In relation to that figure, the following remarks can be noted:

- The solar gain effect is frequently overestimated by the ARX model (the predicted inside air temperature is higher than the real one), but not by the ANN model. This can be explained by the non-linearity of solar gains relative to the incident solar radiation, due to the user's behaviour (pulling down the blind when there is too much solar radiation, or possibly opening the window), and the ability of the ANN model to deal with such non-linearities.
- During the first two days, the window has been kept open, which explains the large variations of inside air temperature and the bad predictions of all the models, especially the ARX model. The inclusion of such data in the training example base emphasises the inefficiency of linear models: a large value of temperature gradient gives a high contribution to the total deviation for a linear model, while such a case can be taken into account much better by a non-linear model.

2.4.2 Additional conditions for the building model

Finally, the ANN model has been chosen for the NEUROBAT controller. Nevertheless, it has appeared that the ANN building model can provide erroneous information to the optimal controller, especially concerning the heating power dependency. For instance, while the future temperature in function of the heating power must follow a strictly increasing function in all the cases for physical reasons, the ANN, as trained on the sample base, exhibits some non-physical characteristics for some space regions which are not (or not enough) explored by the samples, typically a decreasing function for the predicted temperature versus the heating power. This is not acceptable, since it can lead the optimal controller to a wrong solution or to a divergence, because the optimal controller scans situations that are not realistic (for example heating when Toutside is 25 °C), but which must be handled correctly and still keep a physical sense.

In order to make the behaviour of the model better in the regions which are not supposed to be met normally, or which are met rather infrequently, two complementary approaches have been used simultaneously. They allow to avoid spurious commands from the NEUROBAT controller. The first approach is the use of constraints on the ANN weights (see [1]). The second approach is the spread of the training example base over the whole input space: keeping in memory all the examples, even those which do not happen frequently, allows to fill nearly completely the whole input space (see section 5).

2.5 Dynamic programming optimal control algorithm

2.5.1 Cost function

The algorithm aims at optimising thermal comfort and energy consumption over a fixed time horizon (6 hours in the NEUROBAT controller). The optimisation is done through the minimisation of a "cost function", taking into account both aspects, and integrated over the time horizon. Several authors (see for example [4], [9], [12], [13], [14], [15]) have already applied optimal control theory to building heating systems. The mathematical expression of the cost function used for the NEUROBAT controller is described hereafter:

$$J(U,T) = Cu \cdot U + Cp \cdot (\exp(PMV^2)-1)$$

where: U = heating command [W]

PMV(T) = Predicted Mean Vote on the Fanger's scale (see below)

T = comfort temperature [°C]

Cu = weighting coefficient for the heating energy term

Cp = weighting coefficient for the thermal discomfort term

The complete description of the cost function is given in [4]. The two terms of the right hand side in the expression of the cost function are corresponding to the inconvenience respectively of the heating energy consumption and of the thermal discomfort felt by an "average user". The thermal discomfort is expressed by the deviation from the optimum PMV ("Predicted Mean Vote"), given by the Fanger's formalism [16], on a scale spreading from -3 (very cold) to +3 (very hot), with 0 being the neutral (optimum) thermal comfort condition.

The correct weighting of the two cost function terms is achieved by using a simple heuristic rule: "The cost of the energy consumption which is needed to compensate a 0.2 variation on the PMV is equal to the cost of the discomfort resulting from that same PMV variation." That rule takes into account the effective thermal capacity of the building (or of the considered room). If we fix an arbitrary value of Cp equal to 1 (only the ratio between Cu and Cp has a significance), then the value of Cu is given by the expression below:

$$Cu = \Delta t \cdot k \cdot (\exp(\Delta\,PMV^2) - 1) / (Cdyn \cdot \Delta\,PMV)$$

where: Δt = considered time interval during which the heating power is applied [s]

k = linear constant for the PMV linear approximation: PMV = k · (T - Topt)

T = room temperature [°C]

Topt = room temperature for the optimal thermal comfort (PMV = 0) [°C]

Cdyn = effective (dynamic) thermal capacity of the room [J/K]

In order to take into account the user presence, the coefficient Cp is fixed to 1 when the user is present, and to 0 when the user is not present in the room (in that latter case, there is no need to provide thermal comfort, and the only "cost" should be the energy consumption).

2.5.2 Optimal control

The optimal control receives the information from the building and climate models to elaborate an optimal heating command sequence over the next 6 hours (optimisation time horizon). At each time step (15 minutes), the following information is available:

- the current and past state of the building (temperatures Ti(k) and Ti(k-1));
- the predicted profile of the solar radiation on the window surface for the 6 next timesteps (G(k+1), ... G(k+6));
- the predicted profile of the outside air temperature averaged over the last 24 hours Te(k+1), ... Te(k+6)).

At each new timestep k, the optimal command u_k^* is the command which minimises the cost over the time horizon (n timesteps):

$$H = \sum_{m=k}^{k+n} J(u_m, T_{m+1})$$

The calculation of u_k^* uses the dynamic programming algorithm, which is described in detail in [17] or [18]. The method allows to find a global minimum, but requires a lot of computing power: a balance must be found between a more detailed discretisation of the state variable (Ti) and heating command (u), and a too intensive use of the CPU which would not allow to recalculate the optimal command at each timestep.

3. SIMULATION

3.1 Simulation program

A simulation program has been developed and used for complementing the experimental results. The program allows to simulate the thermal behaviour of one room during a period of a whole year. The program includes a nodal network equivalent of the room itself (28 nodes), plus additional nodes for the heating subsystem (4 nodes), and assigned temperature nodes to model the neighbour rooms and the outside air.

The program has been developed in the framework of the DELTA project, and is described in detail in the corresponding final report [19]. It has been thoroughly validated on experimental data. Since the same rooms have been used in the NEUROBAT project, with the addition of a new heating system similar to a traditional central heating (see section 4), only the heating system model has been added to the simulation model.

The Matlab software has been chosen for the programming, because of its rich collection of library functions for artificial neural networks and fuzzy logic. A graphical interface has been built, allowing an easy display of the various system variables (temperatures, powers, blind position, room occupancy, etc).

3.2 Simulation conditions

For the simulation, real measured data (outside air temperature and solar radiation on a horizontal surface) measured in Lausanne for the years 1981 and 1982 has been used.

The blind position α (1 = completely open, 0 = closed) has been calculated from a correlation with the solar radiation incident on the window surface, as established during the project DELTA [19] which included measurements on the same office rooms (for $S < 100$ W/m^2, $\alpha = 1$; for $S > 450$ W/m^2, $\alpha = 0.2$; α interpolated linearly between these two values).

The artificial lighting requirements are evaluated from the illuminance on the user's desk, which was located 2.5 meters away from the window. The daylighting is evaluated using the "daylight factor" method, with additional provision for the blind position (daylight factor depending linearly from the blind position). Then the artificial lighting (the characteristics of the luminaires are given in [20]) is used to complement the daylighting, if needed.

For the internal gains, a constant value of 100 W during the occupation, corresponding coarsely to one person (and no electric appliance, except the artificial lighting), is used. Concerning the occupancy, a fixed schedule 8:00 - 18:00 during the weekdays, and no occupation during the weekends (Saturdays and Sundays), is considered.

3.3 Simulation results

In order to be able to compare and assess the performance of the NEUROBAT heating controller, different heating controller simulation models have been implemented and simulated. The table V below summarises the commercial controller variants simulated (others variants have been also taken into account, given in [1] or [3]). They are based on the principle of the heating curve, with extensions concerning the internal temperature adaptation, the start/stop algorithm, the control parameters adaptation, and the inclusion of a solar sensor. These algorithms correspond to modern and advanced controller presently on the market, provided by a leading Swiss manufacturer of HVAC controllers [21]. The table also summarises some of the NEUROBAT variants which have been considered.

TABLE V: Description of the various commercial and NEUROBAT heating controllers used for the simulation

Controller	Sensors			Control concept	Remarks
	Outside temp.	Inside temp.	Solar radiation		
1. Standard commercial controller	yes	no	no	open loop control referenced to the external temperature	common control system; not well suited for buildings
2. Performant commercial controller	yes	yes	no	variant 1 + adaptation to inside temperature and optimal start/stop	suitable for buildings with intermittent operation
3. Very performant commercial controller	yes	yes	yes	variant 2 + adaptation to solar radiation	solar gains taken into account
4. NEUROBAT standard	yes	yes	yes	optimal control + ANN models	basic variant
5. NEUROBAT with ideal meteo prediction	yes	yes	yes	variant 4 + ideal meteo prediction (reading ahead the meteo file)	evaluation of the effect of the real meteo prediction

The different controllers are assessed with reference to the energy consumption, the thermal comfort, the intermittent use management and the commissioning. It has to be noted that the standard commercial controller has been tuned in such a way to reach a similar setpoint temperature during the occupancy, when compared with the other variants, thus simulating a rather careful commissioning (otherwise, it would perform worse than reported in the table VI below).

3.3.1 Energy consumption during one heating season

The global results (energy consumption, comfort cost, solar gains, etc) of the various controllers for the heating season 1982/1983 is shown in table VI below. The adaptive controller variants have been trained on the heating season 1981/1982.

The data common for all the variants is summarised first:

- total simulated time: 212 days
- total occupation time: 1510 hours
- potential solar gains (blinds always open): 4105 MJ
- effective direct solar gains (with "real" blind position): 2395 MJ
- artificial lighting consumption: 425 MJ
- internal gains (persons and appliances, except artificial lighting): 544 MJ

The Table VI gives, for each variant, the heating energy provided to the hydraulic circuit, the heating energy delivered to the room air (some part of the energy provided to the hydraulic circuit is lost in the transmission), the energy cost per day (calculated over the whole day by the same expression as for the cost function, i.e. Σ {Cu $\cdot$ U}, U being the heating command), and the thermal comfort cost per day (or more exactly, the cost connected with the thermal discomfort, calculated over the scheduled occupation time 8:00 to 18:00, by the same expression as for the cost function, i.e. Σ {Cp $\cdot$ (exp(PMV^2)-1)}, PMV being the Predicted Mean Vote derived from the room temperature). The last index gives a relative estimation for the thermal comfort level which can be reached by each controller.

TABLE VI: Global simulation results of the commercial and NEUROBAT controllers

Variant	Heating (water) [MJ]	Heating (room) [MJ]	Energy cost/day [-]	Comfort cost/day [-]
Standard commercial controller	1626	1477	0.03	3.68
Performant commercial controller	1183	1073	0.02	1.49
Very performant commercial controller	1177	1068	0.02	1.47
NEUROBAT standard	1048	951	0.02	1.09
NEUROBAT with ideal meteo prediction	1082	981	0.02	1.08

Some remarks and explanations about that table are given in the following:

The standard commercial controller with its energy consumption (1626 MJ) and its comfort (comfort cost 3.68) is far from optimal.

The adaptation of the heating curve parameters to the internal temperature and the optimal start/stop algorithm of the performant commercial controller enables a considerable reduction of the energy consumption (down to 1183 MJ) and the optimisation of the thermal comfort (comfort cost 1.49).

The introduction of a solar radiation sensor (very performant commercial controller) does not increase substantially the performance: the energy consumption and the comfort cost are nearly equal to the results of the performant commercial controller. Indeed, the information of the additional heat gains is already covered by the room temperature sensor. The performance increase would have been more significant if we add a solar sensor to the standard commercial controller.

The NEUROBAT controller allows a significant improvement of the performances: the energy consumption is reduced to 1048 MJ (11 % reduction when compared to the most performant commercial controller) , and the comfort cost to 1.09 (27 % reduction).

The NEUROBAT controller variant with an ideal meteo prediction consumes slightly more energy (+ 3 %). This surprising result is due to the way the meteo prediction ANN of the controller calculates the prediction: during the morning, the solar gains predicted by the ANN are slightly overestimated, which leads to a lower energy consumption than if the prediction would be perfect (but also to a slightly degraded thermal comfort).

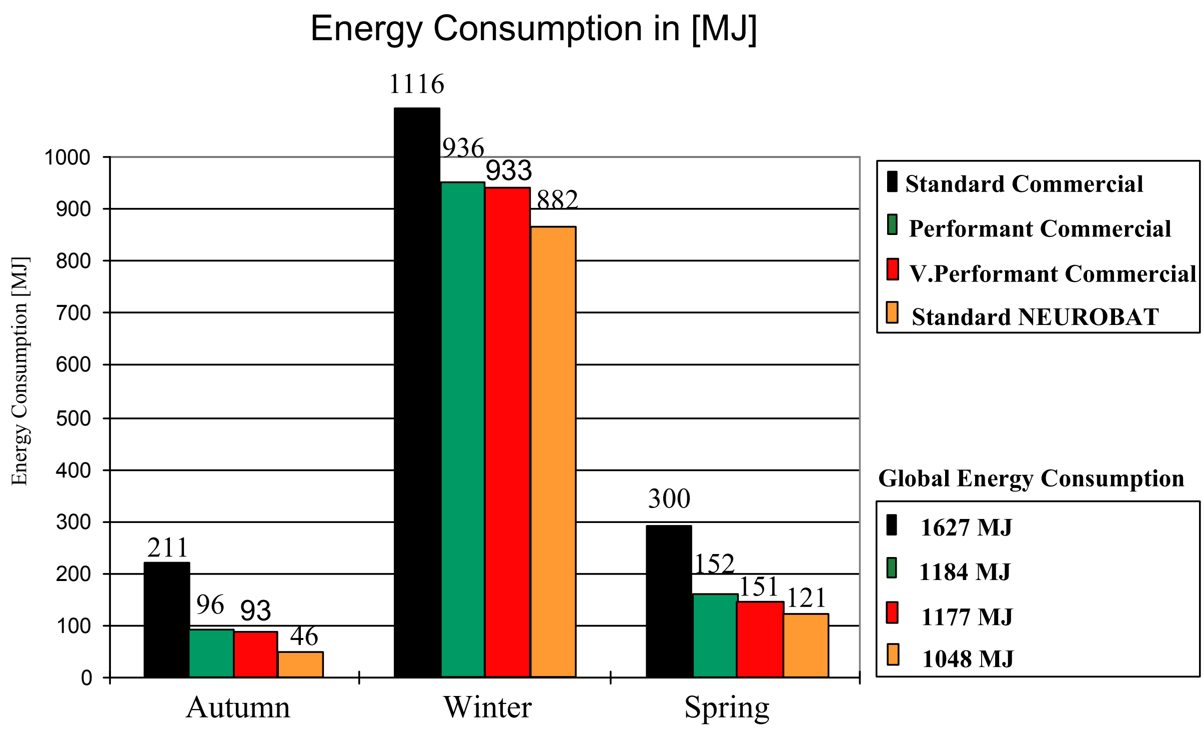

Figure 3: Energy consumption simulation results, for several controller variants

The Figure 3 shows a graphical comparison between several variants. It emphasises the fact that the NEUROBAT controller operates the most efficiently during the mid-season, with a variable meteo data, and allows to profit optimally from the free heat gains.

3.3.2 *Heating profile*

The daily profile of the heating power depends heavily on the controller algorithm. The three Figures 4 to 6 below show a comparison between the standard commercial controller, the performant commercial controller, and the NEUROBAT controller, averaged during the whole winter or during one month (January or March).

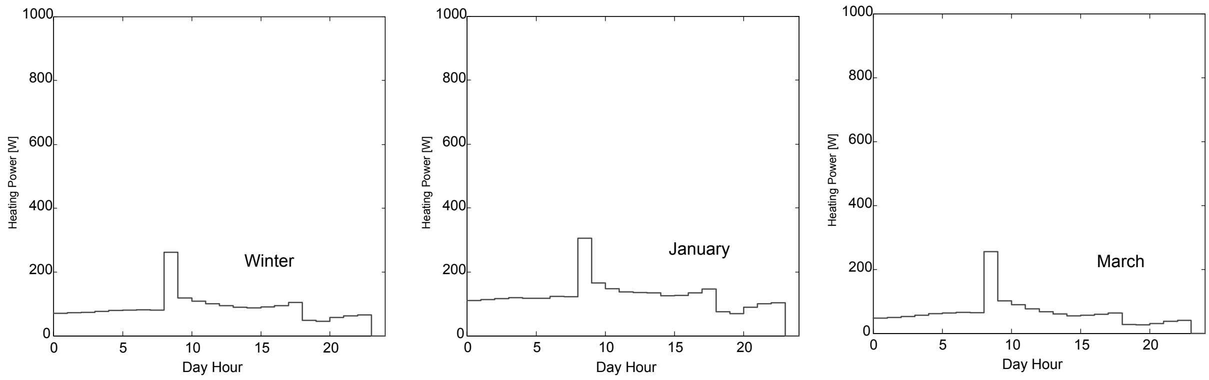

Figure 4: Average value of heating power daily profile, for standard commercial controller

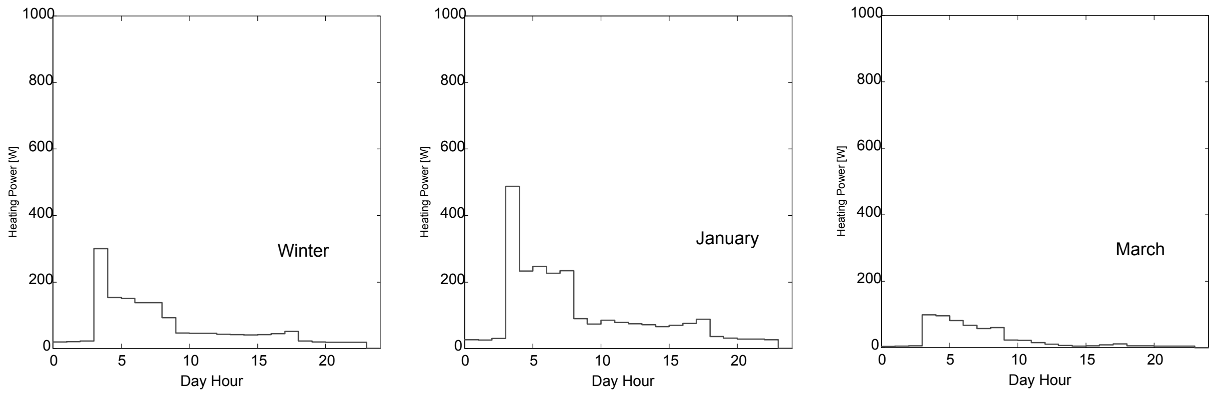

Figure 5: Average value of heating power daily profile, for performant commercial controller

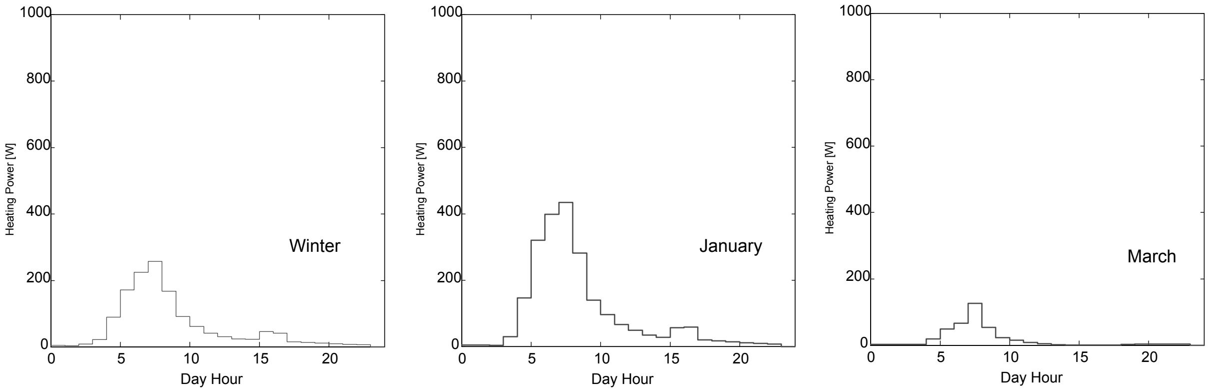

Figure 6: Average value of the heating power daily profile, for the NEUROBAT controller

The standard commercial controller provides the maximum heating power at the beginning of the comfort period; during the rest of the day, the heating power remains nearly constant, and no optimisation regarding the user's time schedule is done. The performant commercial controller delivers the maximum heating power during the early morning period, several hours before the start of the occupation period, in order to anticipate the comfort requirement; the heating power is strongly reduced during the afternoon. Finally, the behaviour of the NEUROBAT controller shows its predictive features: during the winter period, the heating power anticipates the comfort requirement but with some time delay in comparison with the performant commercial controller; during the time period 10:00 to 15:00, the heating power is reduced, then afterwards put back to a higher level in order to avoid a drop-out of the room temperature.

3.3.3 Thermal comfort

For a more detailed comparison than with the thermal cost function, as displayed in a preceding section, PMV (Predicted Mean Vote) histograms can be shown. The following figures give comfort histograms for the whole winter, January, and March, during the presence hours, for the standard commercial controller (Figure 7), the performant commercial controller (Figure 8), and the NEUROBAT controller (Figure 9). The narrower and more centred on 0 the histogram is, the better the thermal comfort is.

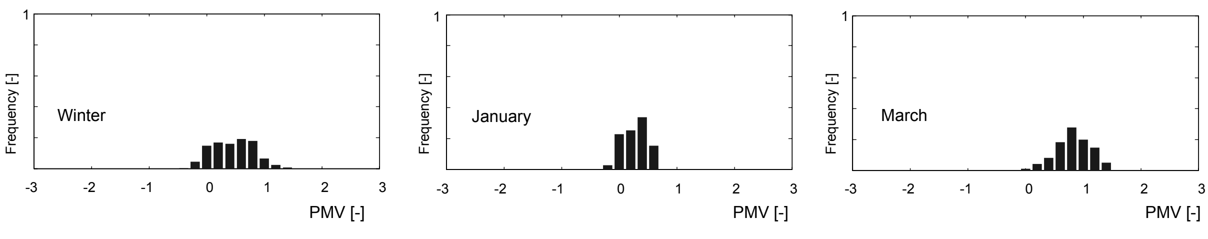

Figure 7: PMV histograms for the standard commercial controller

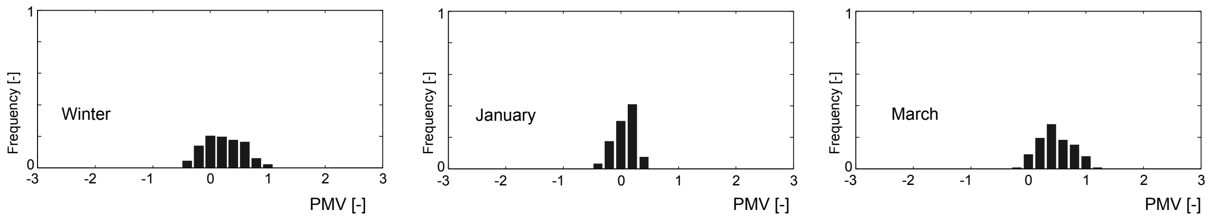

Figure 8: PMV histograms for the performant commercial controller

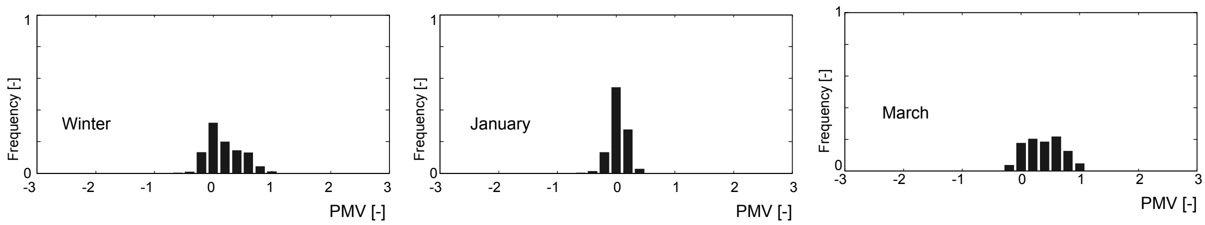

Figure 9: PMV histograms for the NEUROBAT controller

The following comments can be given:

- For all the variants, the comfort can be regarded as sufficient, except for the standard commercial controller, for which the PMV is too often larger than 1 (a bit too hot) in March.
- Compared with the standard commercial controller, the performant commercial controllers delivers a much better comfort (histogram more centred near the zero value, i.e. the optimal comfort).
- Compared with the performant commercial controller, the NEUROBAT controller gives a small comfort improvement, reducing the dispersion around the optimal comfort zero value.

4. EXPERIMENTAL TESTS

4.1 Experimental test set-up

The performances of the NEUROBAT controller has been checked experimentally during the heating seasons 1996/1997 and 1997/1998 on a real size inhabited building, the LESO building of the Federal Institute of Technology in Lausanne (EPFL). The building is made of nine "thermal units" insulated one from the others, and each unit has a particular facade, oriented towards plain South [22]. The thermal unit situated in the centre ground floor includes two similar office rooms, separated by an insulated wall, which have been used for the NEUROBAT experimental tests. The two rooms are numbered 03 (towards East) and 04 (towards West). The characteristics of room 03 are given in the table VII below (the characteristics of room 04 are similar, but the East and West walls are exchanged).

TABLE VII: Thermal characteristics of Room 03

	Component	Area [m^2]	Layers (from inside to outside)
South facade	glazing	3.77	triple glazing 4/12/4/12/4 mm, U-value = 2 W/m^2K
	window frame	2.85	U-value = 3 W/m^2K
	heavy outside wall	3.55	concrete (14 cm) / glasswool (10 cm) / ventilated air layer / aluminium cover
East partition	heavy wall	14.6	concrete brick (10 cm) / glasswool (10 cm) / concrete brick (10 cm)
West partition	light wall	14.6	plaster panel / glasswool (8 cm) / plaster panel
North partition	heavy wall	7.5	concrete brick (10 cm) / glasswool (8 cm) / concrete brick (10 cm)
	door	2	wood (5 cm)
Horizontal partitions	ceiling	15.6	concrete (25 cm) / insulation (6 cm) / chape (6 cm) / plastic coating (0.5 cm)
	floor	15.6	plastic coating (0.5 cm) / chape (6 cm) / insulation (6 cm) / concrete (25 cm)

The rather low thermal exchange with adjacent rooms, compared to the exchange with the outside, allows to consider each room as thermally insulated from the rest of the building.

The outside facade is oriented towards South, and the window area / floor area ratio is important (24 %); the passive solar gains are therefore significant. The solar protections are outside textile blinds of mediocre quality (energy transmission 20 % when completely closed). They are motorised, which allows the possibility of an automatic control (such a control has been implemented, on the same office rooms, during the DELTA project [19]). During the NEUROBAT experimental tests, the blinds were controlled by the users.

The air change towards outside, when the window is closed, is around 0.1 vol/hour [23]. The window opening is left up to the users.

The availability of two independent rooms allows to make comparisons between a conventional controller (the advanced commercial controller used in the simulation study) and the NEUROBAT controller, by simultaneous use of both controllers, one in room 03 and the other in room 04. In order to cancel the bias due to different users, and possibly slightly different thermo-physical room characteristics, both rooms have been regularly interchanged (at about 2 or 3 weeks interval) during the comparative tests.

Besides the building itself, the experimental set-up includes two basic components:

- the data acquisition system, which monitors the whole building through sensors placed at various locations in the building;
- the controller system, which implements the control algorithm using its own sensors.

4.1.1 Data acquisition system

Around 50 sensors located in the experimental rooms (temperatures, opening status of doors and windows, heat flows, water flows, electricity power, occupancy, illuminances) and on the building roof (for the weather data: temperatures, solar radiation, illuminance) allow a continuous monitoring of the experiment.

The VNR data acquisition system [24], based on a PC (IBM-compatible Personal Computer) connected to the Ethernet PC network of the building, measures the data every minute, and sends the available data on request from the other PC (see below), through the Ethernet link.

4.1.2 Controller system

The controller system is implemented as a PC software, connected to the experiment through an I/O module. It includes two main blocks:

- A real time control module handles the acquisition of control sensors (every minute), the control of the mixing valves, the user interface to the experiment, and the recording of data on disk files (every 15 minutes). The module also reads the monitored data from the VNR data acquisition system and rewrites the data on the same disk file as the heating controller data, in such a way as to have both data available on the same file for convenience. The module has been elaborated with the measurement and automation software Labview.
- The heating controller module calculates, every 15 minutes, the heating power to apply to the heating system. In order to be able to make a comparison, both the advanced commercial controller [21] and the NEUROBAT controller (calculating an optimal command over a 6 hours time horizon) have been implemented. The module is written in Matlab language and is identical to the corresponding module of the simulation software.

The sensors needed for the control algorithm (room temperature, radiator inlet and outlet temperatures, presence sensor, for each room; outside temperature, global horizontal solar radiation, for the weather data) are connected to the controller PC through a dedicated I/O module.

The complete block diagram of the experimental set-up is represented on the Figure 10 below.

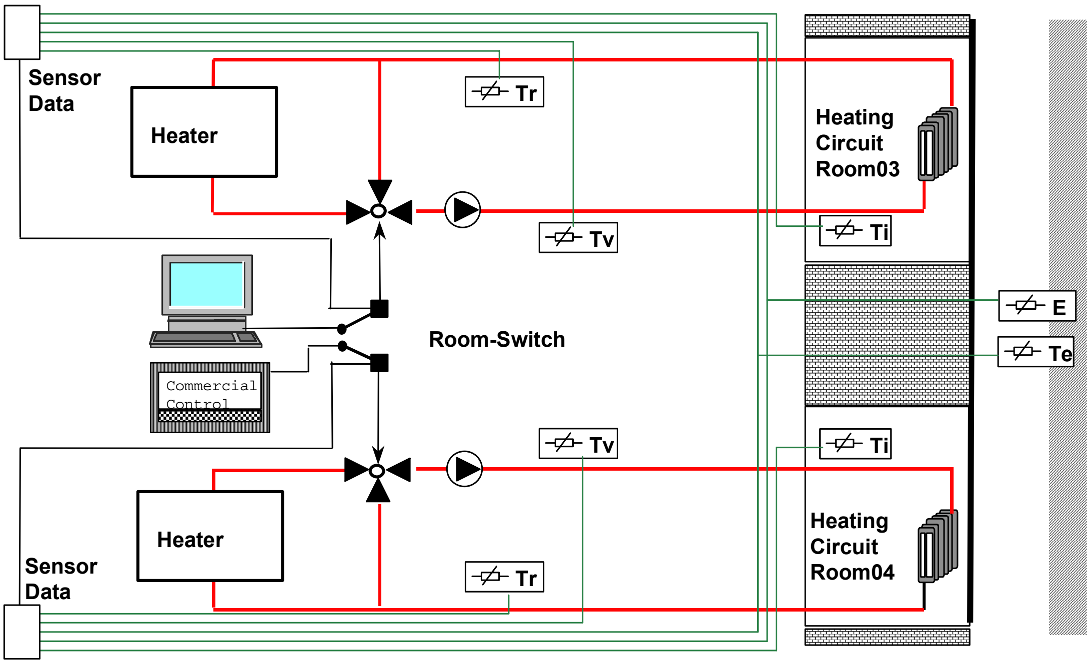

Figure 10: Block diagram of the experimental set-up. A switch allows to exchange the NEUROBAT and reference controller between the rooms 03 and 04. Sensors: Tv = inlet temperature, Tr = return temperature, Ti = room air temperature, Te = outside temperature, E = global solar radiation on a horizontal surface

4.1.3 HEATING EQUIPMENT

Both rooms have been equipped with conventional water radiators with small individual boilers, which simulate the traditional central heating equipment most commonly found in Switzerland.

4.2 Experimental test results

4.2.1 Heating energy consumption comparison

Every two or three weeks, the controllers (NEUROBAT and reference) are exchanged between the two rooms, in order to avoid a systematic bias due differences in the user's behaviour and the thermal characteristics of the rooms. The table VIII below gives a summary of the results for the year 1997 (January to April during the winter 1996/1997, and October to December during the winter 1997/1998), after elimination of the days used for special tests (calibration, heating during night, passive cooling during the week-end, etc), and the days where the heating controller and/or the data acquisition system did not operate properly. It displays the following data:

- the heating (water) is the electric energy used to heat the boiler;
- the heating (room, measure 1) is calculated by subtracting from the preceding data the estimated heat losses by the boilers and the part of the piping situated in the cellar, and transmitted to the cellar rather than to the test room;
- the heating (room, measure 2) is calculated by the temperature difference between the inlet and return hot water, multiplied by the water mass flow rate [kg/s] and the water thermal capacity [J/kgK];
- the actual solar gains are taking into account the real blind position, the potential solar gains are the gains if the blind would be always in the fully open position;
- the energy cost per day is calculated over the whole day by the expression used in the optimal control cost function;
- the thermal discomfort cost per day is calculated by the expression used in the optimal control cost function (from Fanger's PMV), only during actual (measured) occupation.

Table VIII: Global results for the year 1997. Both measurements of heating (room, measure 1 and room, measure 2) should be identical, within a margin equal to the experimental error margin.

	Neurobat room 03	Reference room 03	Neurobat room 04	Reference room 04
Measured time [days]	80.6	65.6	65.6	80.6
Occupation time [hours]	263.4	229.2	244.0	271.5
Heating (water) [MJ]	1147	1074	632	927
Heating (room, measure 1, see above) [MJ]	952	895	458	713
Heating (room, measure 2, see above) [MJ]	918	873	403	696
Actual solar gains [MJ]	712	522	486	753
Potential solar gains [MJ]	1383	975	975	1383
Energy cost per day [-]	0.20	0.24	0.11	0.15
Thermal discomfort cost per day, during occupancy schedule [-]	6.50	2.57	2.63	8.15
Thermal discomfort cost per day, during actual occupancy [-]	0.48	0.53	0.74	1.69

The Figure 11 below gives the average power for the most significant heat contributions, for the four possible configurations of the control system.

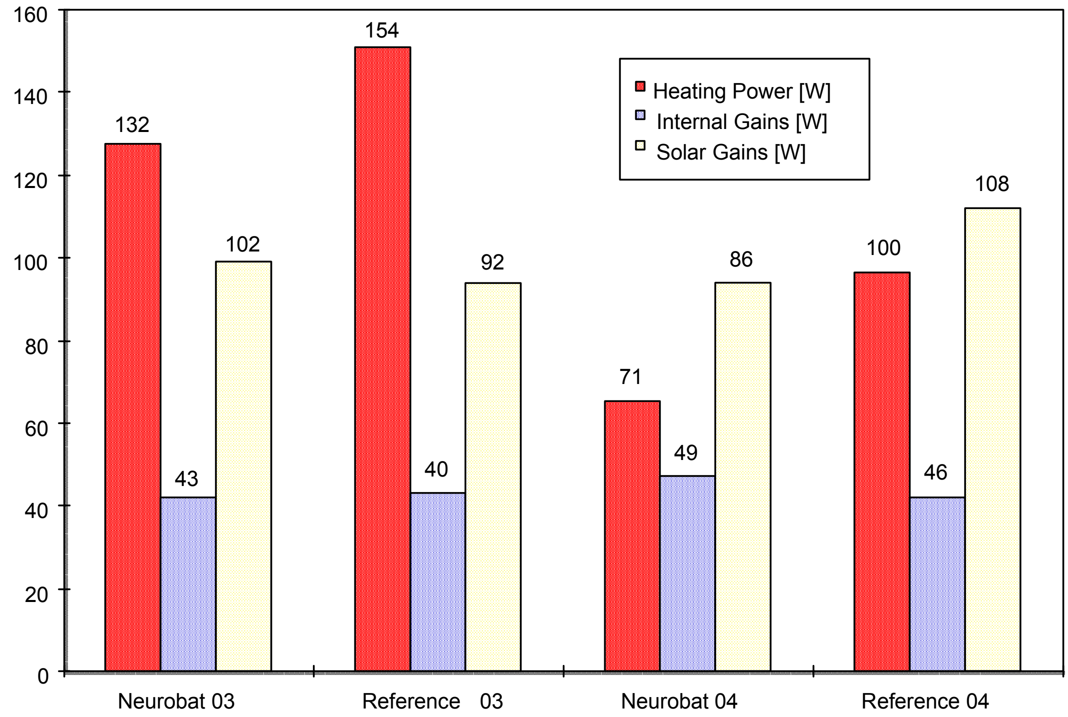

Figure 11: Most significant heat contributions for the four possible configurations of the heating control system (numbers are given as average power in [W])

From that figure, the following statements can be issued:

- The heating power used by the room fitted with the NEUROBAT controller is significantly lower than the heating power used by the other room, independently of the room considered.
- The room 03 has a higher heat demand than the room 04. A test carried on after the NEUROBAT measurements has shown that the outside facade of room 03 has an air leak (which has been obstructed for the measurements during heating season 1997-1998), and an infrared thermography has revealed a small thermal bridge. Thanks to the systematic exchange between the two rooms, that small asymmetry has no severe consequences on the experimental results.

- In order to be able to compare both systems and to eliminate the bias due to the different thermal characteristics and user's behaviours, the energy consumption has been summed over the whole measurement period, then again averaged:

  P(NB) = (E(NB,03) + E(NB,04)) / (t1 + t2)

  P(ref) = (E(ref,03) + E(ref,04)) / (t1 + t2)

where: P(NB) = average heating power for the NEUROBAT controller [W]

P(ref) = average heating power for the reference controller [W]

E(NB,xx) = energy used by the NEUROBAT controller in room xx (03 or 04) [J]

E(ref,xx) = energy used by the reference controller in room xx (03 or 04) [J]

t1 = time duration with NEUROBAT in room 03 and reference in room 04 [s]

t2 = time duration with NEUROBAT in room 04 and reference in room 03 [s]

TABLE IX: Global experimental results for the year 1997

	NEUROBAT	Reference (performant commercial controller)
Energy consumption [MJ]	1410	1627
Measured time [days]	146.2	146.2
Average heating power [W]	112	129

The final result is given in the Tabel IX. The energy saving provided by the NEUROBAT controller is 13 %, compared with the reference controller. This number is in good agreement with the simulated result (11 %).

An evaluation by season (mid-season, winter) shows that for mid-season, the relative saving can be much higher (until more than 50 %), for the following reasons:

- the solar gains at the beginning or end of the heating season are more important, and the NEUROBAT controller handles these gains more smartly;
- for the end of the heating season, the prediction models of the NEUROBAT controller (weather and building) have been made better by training during the whole heating season.

4.2.2 Thermal comfort comparison

Like for the simulation, the thermal comfort hat been evaluated using the Fanger's model. The PMV (Predicted Mean Vote) and the PPD (Predicted Percentage of Dissatisfied Persons) histograms have been evaluated over the whole heating season during the actual occupation. The PMV histograms are given in the two Figures 12 and 13 below.

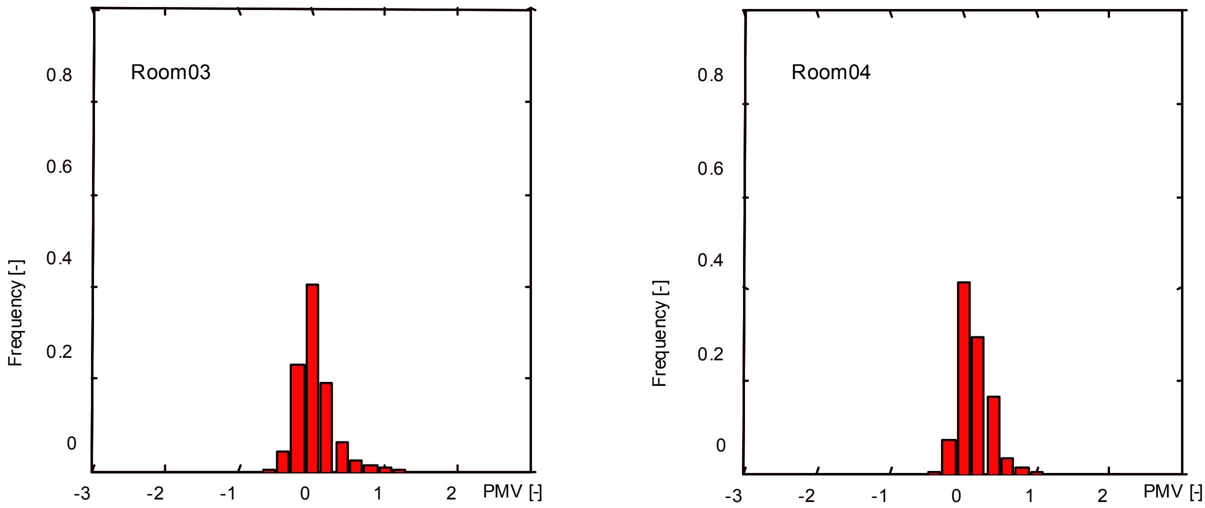

Figure 12: PMV histogram during actual occupation of the room, during the whole heating season, with the NEUROBAT controller

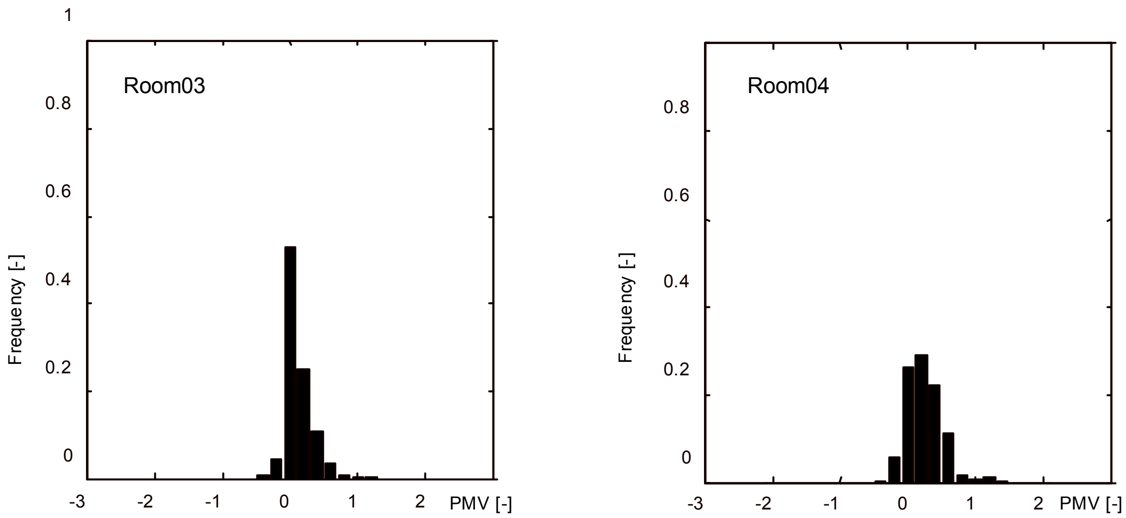

Figure 13: PMV histogram during actual occupation of the room, during the whole heating season, with the reference controller

The thermal comfort is satisfactory in all the cases (the PMV is included in the interval [-0.5,+1]). Both controllers are therefore efficient and provide a good thermal comfort. Nevertheless, the NEUROBAT controller is a bit better, because the PMV histogram is more centred on the optimal value zero (optimal thermal comfort). It has to be noted that the overheating is limited by the users, through window opening or blind lowering.

5. SELF-COMMISSIONING

The commissioning of the technical equipment is very important. A good commissioning can save a lot of energy and at the same time provide a much better comfort for the users (for instance, avoiding overheating or too high ventilation rates, which lead to a high discomfort).

Very often, the commissioning is not well done, sometimes simply "forgotten". The default parameter values for the controllers are used, instead of better values which need a careful tuning by experts.

Thus the interest of elaborating controllers which can adapt themselves to their environment. The neural networks of the NEUROBAT controller offers such a capability: they can progressively "learn" the building model and the weather model, using the values measured by the controller and its sensors during its normal operation.

Nevertheless, when starting a heating equipment, the operation must be correct from the beginning, even when it is not yet optimal. Therefore, it is necessary to initialise the models realistically, i.e. at least as well as in the case of a conventional controller based on a heating curve.

5.1 Initialisation model of the building

The initialisation model must fulfil the two requirements:

A. to give a fair approximation of the building thermal behaviour; for instance, the influence of the main perturbations (solar radiation, outside temperature) must be taken into account correctly;

B. to be defined without a significant calculation effort; the model should not need the introduction of a detailed physical description of the building by the user.

A simple one-node model has been used in our case. The model includes three physical parameters: the thermal loss coefficient of the building towards outside, the equivalent area for solar gain collection, and the effective thermal capacity of the building. Building categories have been defined, considering these parameters, and we have shown that giving the category is enough to provide a correct initialisation model. For more details, please refer to [3].

5.2 Self-learning ANN model of the building

The self-learning process allows the ANN building model to adjust continuously to the reality, as measured by the controller's sensors. Therefore, the controller can take into account the building evolution due to several factors: for instance the seasonal variation of the air change rate, a change of the user's behaviour, or a degradation of the physical characteristics of the building. The self-learning process must conform to the following requirements:

- progressively "forget" the rather inaccurate initialisation by the simple one-node model;
- keep enough "different" learning examples, in order to avoid convergence problems related to extrapolation;
- allow the building model to get better when the knowledge of building thermal characteristics becomes deeper.

In order to fulfil all these requirements, we have proposed to use two distinct example bases, which are updated in a different way:

- The global example base contains a uniformly distributed set of examples spread over the whole input variable space. Each input variable is discretised into classes. At the initialisation, every possible combination of central values in each interval are input to the one-node building model and the output from the model fed back to the corresponding "cell". During the normal operation of the controller, the cell corresponding to the current example is updated. In such a way, examples over the whole input space are kept in the global base. For instance, the season-specific behaviour is kept from one year to the next one, because each season corresponds to different Te and Gv and therefore to different zones in the global example base.
- The "temporary" example base contains all the examples for the last 6 weeks, therefore avoiding the rather low example density of the global example base (spreading over the whole input space of the model). Each time a new example is added (i.e. every hour), the oldest example is removed from the temporary example base.

5.3 Simulation results

In order to evaluate the efficiency of the building model initialisation and training, three comparative simulations have been carried on. The goal is to check:

- whether the one-node initialisation model allows a satisfactory operation of the controller (during the time period where the ANN has few examples or none);
- the time needed to reach a good performance of the ANN model;
- the improvement (thermal comfort and energy saving) which can be achieved when using a self-adaptive model.

TABLE X: Description of the simulations carried out for evaluating the initialisation and the self-learning of ANN building model

	Initial building model	Building model during training	Already trained building model
Initial weights	one-node network model	one-node network model	trained during one year of operation
Global example base	initial	initial, then continuously updated	from one year of operation, then continuously updated
Weather model	initial (without training)	trained	trained
Building model	initial (without training)	trained	trained
Simulation year	1981	1981	1981

The simulation variants are described in the Table X below.

The results of the simulations are given in the table XI below. It has to be noted that the numbers given in that table cannot be compared with the ones of table VI (comparative simulated results for commercial and NEUROBAT controllers over one heating season), because both series of simulations were carried on using rather different boundary conditions.

Table XI: Simulated results over the heating season 1981/1982. The solar gains are calculated from the blind position and from the blind and window characteristics. The potential solar gains are the solar gains if the blind would be kept fully open all the time.

	Initial building model	Building model during training	Already trained building model
Simulation time [days]	212	212	212
Occupation time [hours]	1520	1520	1520
Heat delivered to water [MJ]	1046	1011	988
Heat delivered to room [MJ]	949	917	896
Direct solar gains [MJ]	2575	2575	2575
Potential solar gains [MJ]	4612	4612	4612
Artificial lighting [MJ]	430	430	430
Internal gains [MJ]	547	547	547
Energy cost per day, during the whole day [-]	0.02	0.02	0.02
Thermal discomfort cost per day, during occupancy schedule [-]	2.07	2.03	2.01

On the whole year, the heating used by the already trained model (988 MJ) is significantly lower than the one used by the initial model (1046 MJ). Nevertheless:

- the initial model allows a satisfactory, although not optimal, operation of the controller, even without training;
- the training allows a significant reduction of the heat consumption over the whole year (6 %), even more during the mid-season (18 % in November, 13 % in March), when the passive solar gains can yield a very important part of the room heat demand.

When plotting the monthly energy consumption, it can be also shown that after already two months the consumption of the model currently training catches up the consumption of the already trained model. After that, the monthly consumption is comparable.

6. CONCLUSION

The NEUROBAT research project has shown the interest of using bio-inspired, artificial neural networks and predictive concepts for the control of technical equipment in building. The NEUROBAT project is concerned only by the heating controller, but the basic ideas can be also applied for other technical equipment (cooling, ventilation, artificial lighting, etc).

The NEUROBAT concept is summarised by figure 1: three self-learning artificial neural networks (ANN), one for the building model and two for the climate model, allow a prediction of the variables involved in the heating controller (outside temperature, solar radiation, inside temperature) over a 6-hours time horizon. This prediction is used by an optimal control module, which minimises a "cost function" anticipated over that time horizon, by choosing an optimal heating control sequence for the next 6 hours.

The cost function is a very important building block of the controller. It allows to make a compromise between too high energy requirements and a too high thermal discomfort. The cost function used in the NEUROBAT controller is simply made of two terms: one taking into account the energy consumption over the time horizon, and one taking into account the thermal discomfort integrated over the same horizon. By giving an important weight to the discomfort term, and emphasising the high thermal discomfort by using an exponential function of the Fanger's PMV (Predicted Mean Vote) deviation from optimal comfort, the user's comfort will remain quite acceptable during the room occupancy (when it is anticipated that no user is present, the corresponding discomfort term is discarded from the cost function).

Both simulation and experimental tests have been carried out. The simulation tests have given a 11 % heating energy saving over a whole year, when comparing the NEUROBAT controller with an advanced conventional heating controller (using start-stop optimisation, heating curve correction with the inside air temperature, and control parameter adaptation). The experimental tests have given a 13 % heating energy saving over the whole year 1997 (January to April 1997 and October to December 1997), for the comparison between the same controllers.

The experimental tests have also shown a good acceptance of the controller by the users, except at the very beginning when there were still some problems essentially caused by software bugs.

The commissioning of the NEUROBAT heating controller shows also an important advantage of a self-adaptive controller, by avoiding the otherwise requested involvement of building experts. In the reality, a serious commissioning by good experts is done very rarely, therefore causing frequent problems including an over-consumption of energy and/or a high thermal discomfort. A self-commissioning controller can therefore make the controller adaptation to the building and to the user's behaviour much better. It has been shown that the controller operation is satisfactory from the beginning and optimal after around two months.

Nevertheless, some issues will need further investigations, for instance:

- extending and checking the NEUROBAT algorithm to a whole building thermal zone instead of only one room;
- implementing a real user's interface;
- reducing the number of sensors needed (solar radiation, presence);
- finding an algorithm less calculation-intensive than the dynamic programming used for the optimal control (this issue will be especially raised if simultaneous control of several rooms need to be handled by only one controller or micro-controller);
- integrating several controllers for handling various technical equipment related to energy and comfort; integrating several aspects together means not only superposing individual controllers, but aiming at finding a good compromise between all comfort conditions (for instance thermal comfort, air quality, visual comfort) and the energy consumption.

Some of these issues will be investigated during the phase 2 (industrialisation) of the NEUROBAT project. Other ones will be tackled in other research projects to extend the application of the NEUROBAT control concept. For instance, the integration issue (controlling simultaneously the heating, the cooling, the ventilation, the blinds and the artificial lighting) is currently under investigation in the framework of the EU Joule EDIFICIO project [25].

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