Development of a Neural Network-based Building Model and Application to Geothermal Heat Pumps Predictive Control

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***Abstract* - The use of artificial neural networks in the field of building energy management has led to remarkable results over the recent years. In this study, the development of room temperature neural network models, to be used for predictive control of geothermal heat pump systems, is discussed. The training process, including the determination of optimal input data, algorithm and structure, is detailed. The prediction performance of the developed neural network is compared to linear ARX models. Simulated data used for training and validation is generated using the TRNSYS environment. The developed model is then implemented into a predictive controller for geothermal heat pumps systems. Simulation results showed that the predictive controller can provide up to 17% energy savings in comparison with conventional controllers.**

Keywords - Artificial neural networks; Room temperature prediction; Predictive control; Energy savings; Geothermal heat pump.

I. INTRODUCTION

This study focuses on the identification of the building thermal behavior with the aim of being used in a predictive control. Three main types of building modeling are usually distinguished. Direct modeling, which assumes that all the characteristics of the building are known a priori, is more appropriate at the design stage of a building. On the other hand, black-box modeling infers description of the building based on observed data only. Gray-box modeling is a combination of the two latter at various degrees. In this article, only black-box models for predictive control of the indoor temperature will be discussed.

Important research was conducted on predictive control strategies and especially on the building model. Linear autoregressive models were first used for prediction by Lute et al [1]. More recently, the use of artificial neural networks (ANN) has significantly increased the prediction performances of models. ANN clearly outperforms linear models for the prediction of room temperature [2, 3]. In our investigation, a number of parameters are different from the existing studies (input parameters, algorithm, performance criteria, prediction horizon, etc.). The main difference lies in the emitter type which is in our case a radiant floor heating. Its high thermal inertia creates a thermal lag that requires a longer prediction horizon. The ANN prediction performances are compared to linear ARX models, which are commonly used for the building model in predictive control.

The developed ANN model is then applied to ground source heat pumps (GSHP) predictive control. With this system, conventional controls often lead to overheating in the afternoon as they do not integrate a prediction of solar gains. On the contrary, predictive control can adjust the heat supply in advance in accordance with a prediction of room temperature and weather data. The operation of the controller is tested by simulation on a residential house. The predictive controller is compared to conventional controllers with respect to energy savings and overheating control.

II. SIMULATION TEST CASE

Simulation data are obtained with the graphically based TRNSYS software. A residential house equipped with a radiant floor heating connected to a geothermal heat pump is simulated during 3 months with a 15 minutes time step. The simulation includes the following components:

- The studied building (Type 56) is the "Mozart house", which is a 99.8 m2 single-family house of single floor area (Figure 1). The building elements have been chosen to correspond to the current French regulation. The external wall is made of 20 cm of concrete and 8 cm of expanded polystyrene (U-value of 0.42 W.m-2.K-1). The glazing area (U-value of 2.43 W.m-2.K-1) covers 15% of the external surface. This multi-zone building is equipped with a centralized radiant floor heating made of 6 cm of concrete and 6 cm of insulation. The internal gains profile is based on a typical profile for a family of 4 persons.

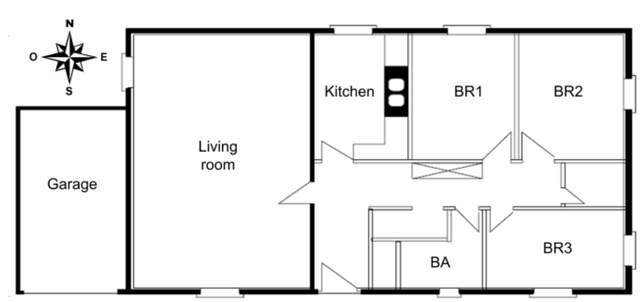

Figure 1: Plan of the "Mozart House" used in simulation

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- The vertical borehole heat exchanger (Type 557b – Tess Library) is made of one 75 m vertical borehole sized using a calculation spreadsheet developed by Philippe [4]. The soil has typical thermal characteristics (cp= 2000 J.kg-1.K-1 and λ= 2 W.m-1.K-1). The double-U pipes have a fluid to ground resistance of Rb= 0.1 K.m.W-1 ;
- Two single-speed pumps (Type 740 – Tess Library) of nominal mass flow rate 1000 kg/h and nominal electric power 80 W ;
- Outdoor conditions are given by a weather data reader (Type 109) for the city of Nancy in France provided by Meteonorm.

III. MODELING PROCESS

A. Models

In this study, ANN models for room temperature prediction over the next 6 hours are developed and compared to ARX models. Various sets of inputs are tested on both types of models.

For each set of inputs, the optimal ANN architecture (number of hidden layers, number of neurons per layer) is determined via a parametric study. In the present study, one hidden layer was always found to be the best solution. The number of neurons in the hidden layer was first chosen to be equal to 75% of the number of inputs [5] and then optimized by trial-and-error until no improvement could be seen. The hyperbolic tangent sigmoid function was used as the transfer function in the hidden layer.

B. Choice of inputs

Various input parameters influence the indoor environment: outdoor temperature, solar radiation, occupation (internal gains, windows opening, etc.), heating power, wind, humidity, etc. Taking into account all these parameters is not conceivable for two main reasons. First, regarding the application on a real controller, the number of sensors would be too high and some variables are difficult to measure. Second, a more complicated model is more likely to diverge as it is more sensitive to noise in the data. The model has to be as simple as possible while taking into account the most relevant inputs. Among all the meteorological variables, the global horizontal solar radiation and the outdoor temperature are accordingly the most influential parameters for the indoor environment.

For nonlinear models such as ANN, there is no systematic approach [6] and the risk of dismissing relevant inputs is high. Statistical methods like auto-correlation criterion or cross correlation give a good insight into the relevance and the lag effect of an input variable on the output.

C. Training process

The parameters of the ARX-models have been identified using the ordinary least squares method that minimizes the quadratic prediction error criteria. As regards ANN, the algorithm used for training was an optimized version of the Levenberg-Marquardt algorithm that included Bayesian regularization. This algorithm minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The generalization capability is also improved with the early stopping feature. In this technique, the collected data that was first normalized to the range [-1; 1] is divided into three subsets: training, validation and test. Training stops when validation performance has increased more than 5 times since the last time it decreased. The test data set is used to estimate the generalization error of the ANN, but does not interfere during the training process.

IV. PREDICTION RESULTS

A. Performance criteria

To evaluate the prediction error of ANN and ARX models, the root mean square error (RMSE) and the mean error (ME) were used as performance criteria:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|\hat{T}_i - T_i\right|^2} \quad (1)$$

$$ME = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{T}_i - T_i\right) \quad (2)$$

The 95% confidence intervals for one-step-ahead forecasts are approximately equal to the point forecast plus or minus 2 times the RMSE (under the assumption of normality). The ME indicates whether the forecasts are biased, i.e. whether the prediction errors tend to be disproportionately positive or negative.

B. Results and discussion

Three months of simulation were used to train and test the models: January and February data are used for training and validation of ANN and ARX models, while March is used for test. A wide range of inputs were tested, but we chose to show only 4 representative set of inputs (TABLE 1), including the set that gave the best prediction performance. The models provide the room temperature $\hat{T}_i$ for the next time step from weather data (outdoor temperature T_o and global horizontal solar radiation I) as well as previous and current values of heating power P_h and room temperature T_i. Tests not presented here revealed that the mean value of outdoor temperature on the last 24 hours To_{24} contains enough information to describe the dynamic behavior of this specific building. For less insulated buildings, the impact of outdoor temperature is higher and the current value of T_o is likely to be more appropriate.

TABLE 1. INPUTS GIVEN TO ANN AND ARX MODELS FOR ROOM TEMPERATURE PREDICTION

Inputs	ANN1/ARX1	ANN2/ARX2	ANN3/ARX3	ANN4/ARX4
I(k)	x	x	x	x
I(k-1)	x			
$P_h(k)$	x	x	x	x
$P_h(k-1)$	x		x	
$To_{24}(k)$	x	x	x	x
$T_i(k-1)$	x	x	x	x
$T_i(k-2)$	x		x	x

TABLE 2. PREDICTION ERRORS OF ROOM TEMPERATURE OVER A 6 HOUR PREDICTION HORIZON

Prediction horizon	1 h		2 h		3 h		4 h		5 h		6 h		Total	
Error [°C]	*ME*	*RMSE*	*ME*	*RMSE*	*ME*	*RMSE*	*ME*	*RMSE*	*ME*	*RMSE*	*ME*	*RMSE*	*ME*	*RMSE*
ANN1	0.02	0.13	0.04	0.25	0.07	0.35	0.10	0.42	0.13	0.49	0.15	0.53	0.52	2.17
ANN2	0.04	0.20	0.08	0.32	0.12	0.42	0.16	0.52	0.20	0.61	0.25	0.69	0.86	2.75
ANN3	0.02	0.12	0.03	0.23	0.06	0.31	0.09	0.39	0.12	0.44	0.14	0.49	0.46	1.99
ANN4	0.02	0.12	0.04	0.31	0.07	0.42	0.10	0.46	0.12	0.48	0.14	0.50	0.48	2.30
ARX1	-0.05	0.41	-0.12	0.53	-0.19	0.66	-0.24	0.74	-0.27	0.79	-0.29	0.80	-1.17	3.92
ARX2	-0.11	0.35	-0.22	0.53	-0.32	0.70	-0.43	0.84	-0.53	0.96	-0.64	1.04	-2.25	4.42
ARX3	-0.05	0.40	-0.12	0.51	-0.19	0.64	-0.23	0.71	-0.26	0.75	-0.27	0.76	-1.11	3.76
ARX4	-0.06	0.40	-0.13	0.52	-0.19	0.64	-0.24	0.72	-0.27	0.76	-0.27	0.76	-1.16	3.80

As the models time step is one hour, the prediction is iterated several times to return up to a 6 hour forecast. TABLE 2 shows the prediction performances of the different models over a prediction horizon from 1 to 6 hours. The following comments can be made:

- ANN models clearly outperform ARX models in terms of ME and RMSE over the whole prediction horizon. The RMSE is in average 40% lower using non-linear ANN models. ANN forecasts are less biased as the ME is smaller in absolute value.
- Too complicated models, such as ANN1 and ARX1, do not give accurate results. On the contrary, ANN2 and ARX2 are too simple to describe the dynamic behavior of the building.
- ANN3 and ARX3 are the most accurate models given both criteria. Previous values of heating power $P_h(k-1)$ as well as room temperature $T_i(k-1)$ and $T_i(k-2)$ must be taken into account due to the high inertia of the building and the floor heating.
- Other tests not presented here showed that taking into account previous values further into the past does not improve the prediction performances of both types of models.

An example of 3 hour prediction results of ANN3 and ARX3 models on a representative week of March is given in Figure 2. ANN model reproduces more accurately the thermal behavior of the building in comparison to the linear ARX model. ANN is in particular much better when the building is subject to strong solar gains (first day of Figure 2).

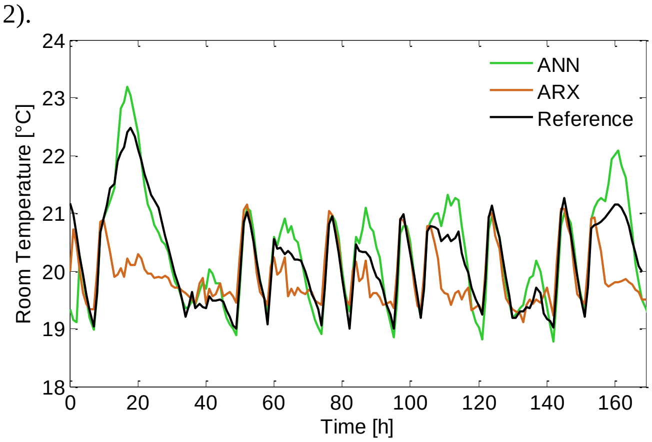

Figure 2. 3 hours prediction of room temperature with ANN3 and ARX3 (March 16-23).

V. APPLICATION TO PREDICTIVE CONTROL

Predictive control can adjust the heat supply in advance in accordance with a prediction of future room temperature and perturbations (solar radiation, outdoor temperature etc.). Important research was conducted on predictive control strategies during the 1980s and 1990s [7-9]. ANN models were successfully applied to the control of residential and small office buildings [10, 11]. The development of predictive controllers for radiant floor heating systems has also led to remarkable results [12-14].

The developed ANN model for room temperature prediction is applied here to single-speed ground source heat pumps (GSHP) predictive control. The concept of the predictive controller, developed by Salque [15], is first introduced. The operation of the controller is then tested by simulation on a residential house and compared to conventional controllers.

A. Concept of the controller

The objective of the controller is to minimize the energy consumption of the GSHP system and maintain a good temperature level anticipating future disturbances and room temperature. The controller is designed to be self learning and easily adaptable in practice. To be compatible with the developed controller, the GSHP system must fulfill the following conditions:

- The GSHP is single-speed (only one single-speed compressor);
- The GSHP only supplies heating and/or cooling (no domestic hot water supply);
- The GSHP is directly connected to the radiant floor heating, without any storage tank for hydraulic decoupling.

1) Controller strucutre

The modular structure of the controller is illustrated in Figure 3.The forecasting modules are all based on ANN. A weather module performs predictions of solar radiation (I) and outdoor temperature (T_o). The heating power produced (P_h) and the electric power consumed by the GSHP (P_{el}) are predicted by another module. The latter uses as inputs the supply and returns temperatures in the boreholes (T_b) and in the radiant floor (T_f), as well as all the possible trajectories of the GSHP on/off for the next 6 hours. The developed ANN model is used for room temperature prediction.

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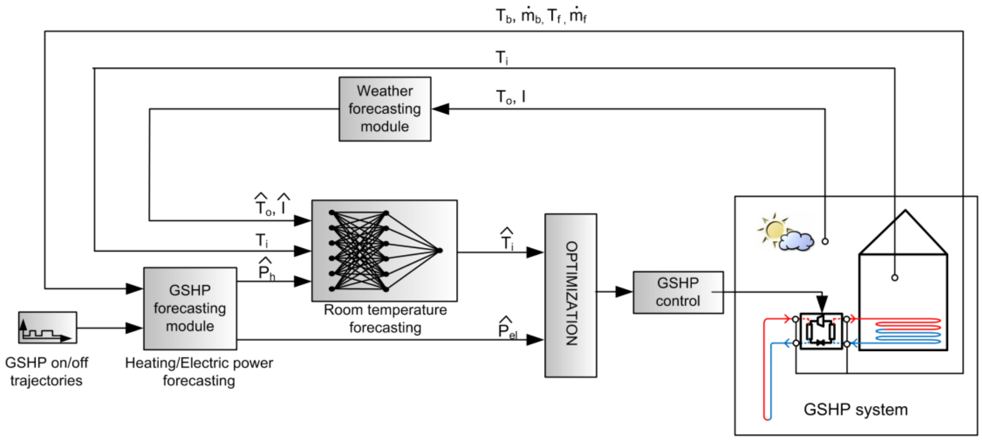

Figure 3. Flow chart of the ANN-based predictive controller. The symbol (^) is assigned to the predicted values.

2) Control strategy

The optimization block determines the optimal trajectory that minimizes the following cost function:

$$J = \sum_{k=1}^{N} \alpha^k \left[\delta(k) \left(\frac{\hat{T}_i(k) - T_r(k)}{\Delta T_{max}} \right)^2 + \frac{\widehat{P_{el}}(k)}{P_{max}} \right] \tag{3}$$

$$\text{subject to} \quad T_{min} < \hat{T}_i(k) < T_{max} \tag{4}$$

where $\hat{T}_i(k)$ and $T_r(k)$ are the predicted and the setpoint temperature, while $\widehat{P_{el}}(k)$ and P_{max} are the predicted and the maximum electric power consumed by the GSHP. The maximal distance to the setpoint ΔT_{max} can be adjusted whether the occupants give more importance to comfort or to energy savings ($\Delta T_{max} = 0.5K$ by default). When the building is not occupied, the condition (4) maintains T_i between T_{min} and T_{max}. For intermittent control strategy, $\delta(k)$ is set to one during the occupancy period and to zero otherwise. α is a value between zero and one (typically 0.8) that gives more weight to the first predictions in time, these being usually more accurate than the distant predictions.

3) Prediction horizon

The length of the prediction horizon depends on several factors. A large horizon is needed when large room temperature or electricity price changes are expected in the future [1]. It is the case in an intermittently occupied building. In practice, the horizon length is chosen as an equivalent of the room time constant corresponding to the first active layers of the walls. For the purpose of the present study, a 6 hour receding horizon is applied.

4) Algorithm

At each time step, the optimal on/off trajectory for the next 6 hours is determined. The discrete nature of the input makes it possible to compute all the possible trajectories and chose the one that minimizes the cost function (3) subject to constraint (4). Moreover, it allows the use of non-linear models, such as ANN, that usually limit the possibilities of analytical problem solving [16].

B. Test of the predictive controller

1) Reference controllers

Two conventional controllers are used as a reference: a closed loop controller (CL) on room temperature and a compensated open loop controller (COL) on floor heating supply temperature $T_{f,s.}$ These two control logic are the most frequently observed in single-speed GSHP installations.

The CL controller switches on/off the GSHP when room temperature is beyond the temperature setpoint Tr with a standard 1°C hysteresis. A smaller hysteresis loop can lead to relatively better temperature level but it reduces the compressor lifetime by increasing the number of on/off cycles.

The COL controller is based on the following heating curve that is adjusted with the actual value of room temperature:

$$T_{HC} = (-0.22 \times T_o + 24.5) - (T_i - T_r) \tag{5}$$

where T_o is the outdoor temperature and $(T_i - T_r)$ the difference between the actual and the setpoint temperature. The COL controller switches on/off the GSHP when the water supply temperature $T_{f,s}$ is beyond T_{HC} ±2°C. The coefficients of the heating curve were finely tuned to optimize room temperature for this particular case. The compensated open loop control logic requires the pump on the building side to always be working to keep the fluid circulating. The two controllers are represented in Figure 4.

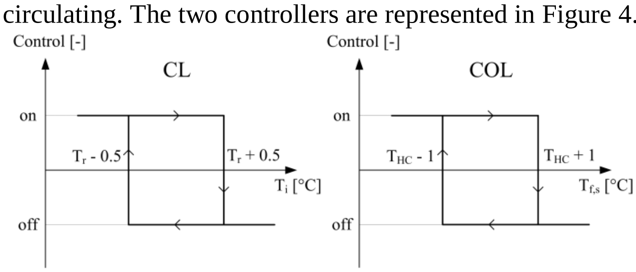

Figure 4. Control logics of the conventional controllers taken as references.

2) Results and discussion

For the purpose of the test, the TRNSYS environment that simulates the GSHP system is coupled to the Matlab software where the predictive controller is coded. January and February data are used to train and validate the ANN models while March is used to test the controller. Two conventional controllers presented above are used as reference: a closed loop controller (CL) on room temperature and a compensated open loop controller (COL) on floor heating supply temperature and outdoor temperature. The temperature setpoint is constant and set to 20°C.

A comparison of the controllers on the first day of March is depicted in Figure 5. CL and COL controllers both lead to overshoots in the afternoon. These conventional controllers actually face the same problem: when the GSHP is switched on in the morning of a sunny day, the indoor environment is likely to be overheated in the afternoon. This is of course due to the fact that both control logics do not integrate a prediction of solar gains. The ANN controller stays closer to the setpoint thanks to its prediction capability. A small undershoot is observed just before strong solar gains are expected so that to avoid overheating and benefit from free solar gains, leading to energy savings.

Over the whole month of March, overheating time (Ti>21°C) is reduced by at least 86% with the ANN controller. The COL controller is generally more efficient than the CL in terms of overheating, but the total electrical energy consumed with the COL logic is much higher with the pump at the building side working permanently. The ANN controller ensures a good temperature level with just 4 hours of overheating above 21°C. Total energy savings achieved are 6% and 17% in comparison with CL and COL controllers.

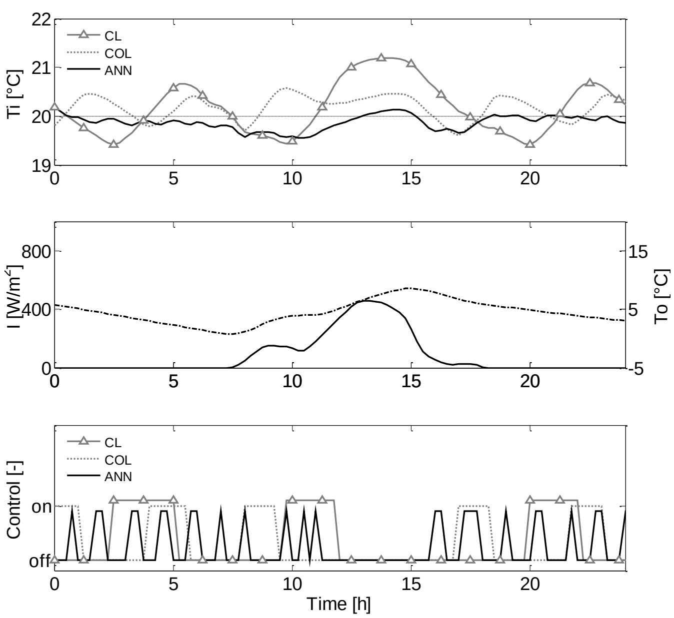

Figure 5. Comparison between predictive controller (ANN) and conventional controllers (CL and COL). From top to bottom : room temperature, weather data (global horizontal solar radiation and outdoor temperature) and GSHP on/off control. March 1st.

VI. Conclusion and Future Work

In this study, the identification of black-box models for predictive control of room temperature in buildings has been discussed. ANN models were developed and compared to ARX models. Various sets of inputs were tested on both types of models. It was shown that the results obtained with ANN are much better than those obtained with ARX models. RMSE on room temperature prediction over a 6 hour horizon is in average 40% lower with ANN. It was also demonstrated that too complicated models do not give accurate results. The model has to be as simple as possible while taking into account the most relevant inputs. Given the high inertia of the floor heating and the building, previous values of heating power $P_h(k-1)$ as well as room temperature $T_i(k-1)$ and $T_i(k-2)$ must be taken into account in the models.

The developed ANN model was then applied to ground source heat pumps predictive control. The operation of the controller was tested by simulation on a residential house and compared to conventional controllers. Numerical results showed that the predictive controller was able to increase comfort and save energy at the same time. Over the tested month, overheating time was reduced by at least 86% thanks to the prediction capability of the controller and energy savings ranged from 6% to 17% depending on the reference controller.

In a next step, this predictive control algorithm will be implemented as a prototype in a real heat pump system. The real heat pump system has already been monitored for one heating season. The performances using the predictive control algorithm can thus be compared to the classic control.

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