Comparison of Single-Speed GSHP Controllers with a Calibrated Semi-Virtual Test Bench

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Abstract — With the recent development of new controllers for heat pump systems, there is a need to test and compare these controllers in a realistic and reproducible environment. This can be done using a semi-virtual test-bench with a simulation environment that is calibrated with in-situ measurements. A real ground source heat pump (GSHP) is connected to the test bench that emulates the building and the boreholes. The test can thus be carried out under dynamic conditions: dynamic weather conditions are used as well as simulated building, floor heating and boreholes. In this study, the developed neural network-based predictive controller is compared to a conventional controller during a one-week semi-virtual test. Test results showed that the predictive controller can provide up to 40% energy savings in comparison with a conventional controller.

Keywords - Artificial neural networks; Predictive control; Energy savings; Geothermal heat pump, Semi-virtual test-bench.

I. INTRODUCTION

Important research was conducted on predictive control strategies during the 1980s and 1990s. More recently, the use of artificial neural networks (ANN) has significantly increased the prediction performances of models. ANN models were successfully applied to the control of residential and small office buildings [1-4]. Other kinds of predictive controllers for radiant floor heating systems have also led to remarkable results [5-8].

Most of these smart controllers were validated by simulation, while some were tested on a real building or on a test cell. Each test technique has its advantages and its disadvantages. The simulation test is required to optimize the controller and to ensure its accurate behavior in various situations. Nevertheless, a simulated environment may not be realistic enough to produce reliable results. Besides, this procedure uses a simulated heat pump. To remedy that situation, the controller can be tested in-situ on a real building or on a test cell. These approaches allow the use of a real heat pump and deals with real noisy data. The main problem of these tests is the fact that two controllers can only be tested sequentially. Even if weather compensation techniques can be done, the comparison generally fails since the conditions (occupants' behavior, weather, etc.) are different. Another comparison technique, called cross-comparison, consists in testing two controllers at the same time but on separate blocks of the same building. Again, the comparison is not accurate since the two blocks can have different internal and external heat gains, orientation or wall composition.

For the purpose of comparing different controllers sequentially and under identical conditions, the semi-virtual test bench PEPSY-PAC [9] developed by the CSTB is used. A real GSHP is connected to a test bench that emulates the building and the boreholes. The test of the controllers can thus be carried out under dynamic conditions: dynamic weather conditions are used as input of a building simulation including floor heating and boreholes. This approach opens a large variety of possible test schedules since the simulated building, the emitter, weather conditions and occupancy can be changed easily. Moreover, the semi-virtual test allows the comparison of different controllers with the same solicitations.

In this paper, the developed ANN predictive controller is compared to a conventional controller during two sequential semi-virtual tests of one week. The simulation environment is designed to reproduce all characteristics (building, weather, boreholes, etc.) of an in-situ GSHP that was monitored during the 2011/2012 heating season in the north of France. The system components parameters (boreholes, GSHP, floor heating and building) are first identified separately then the global simulation with all the components is compared to in-situ measurements.

The paper also includes the description of the ANN controller. The training process including the determination of optimal input data, algorithm, and structure is detailed. The objective of the controller is to minimize the energy consumption of the GSHP system and maintain a good comfort level anticipating future disturbances (solar gains, outdoor temperature) and room temperature. ANN modules are used for the prediction of weather data, room temperature and temperatures in the floor heating and in the boreholes.

The paper is organized as follows. In Section II, the semi-virtual test bench is presented. Section III deals with the calibration of the simulated part with in-situ measurements. The ANN controller is detailed in Section IV. In Section V, the predictive controller is compared to a conventional controller on the bench. The last section presents the conclusions of this paper.

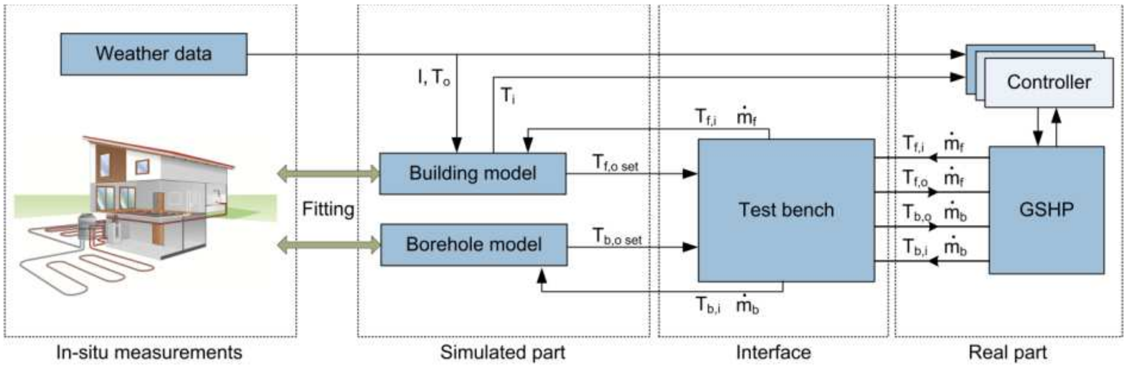

Figure 1: Flowchart of the semi-virtual test of a controller.

II. SEMI-VIRTUAL TEST BENCH

A. Concept of the test-bench

The semi-virtual platform PEPSY-PAC (Platform for the Evaluation of Performances of dynamic SYstems) has been developed for testing performances of GSHP systems or parts of the system [9]. It also allows the test of a controller connected to a real GSHP integrated in a simulated environment, as presented in this paper. This test bench allows the emulation of any water-based heat emitter integrated in a building as well as any kind of ground heat exchanger. The outlet temperature and flowrate of the test bench is controlled by the system simulation.

Matlab is used for the simulated part of the test bench. Simulation is therefore slowed down to real time and the simulation environment enables at the same time the test bench control, system simulation (emulator) and online monitoring of the test.

The operation of the test bench is detailed in Figure 1. Every thirty seconds, the simulated part sends model outputs (outlet temperatures of the floor heating $T_{f,o\text{-}set}$ and the boreholes $T_{b,o\text{-}set}$) to the test bench.

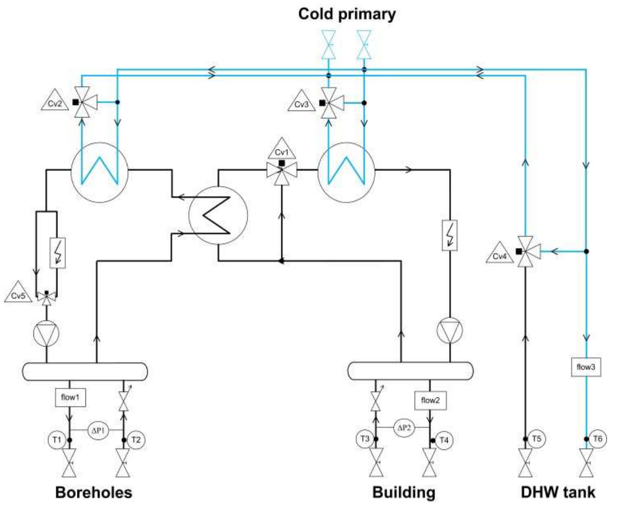

Figure 2: Test bench hydraulic circuit diagram.

The test bench controls the real outlet temperatures of the GSHP ($T_{f,o}$ and $T_{b,o}$) to reach these setpoints. At the same time, the GSHP inlet temperatures ($T_{f,i}$ and $T_{b,i}$) and flow rates ($\dot{m}_f$ and $\dot{m}_b$) are measured and sent to the simulation environment. Weather data like solar radiation I and outside temperature T_o as well as room temperature T_i are transmitted to the tested controller. In-situ measurements, detailed in the next section, are used to fit the simulated part.

B. Construction and control

The test bench integrates 6 hydraulic ports for testing (building, boreholes and Domestic Hot Water tank) as well as 2 hydraulic ports for the cold primary circuit. The DHW tank ports are not used for this test. The circuit diagram is presented in Figure 2.

Seven proportional-integral-derivative (PID) controllers ensure the continuous control of outlet temperatures through the action of hydraulic valves and electric heaters. Figure 3 shows the temperature step responses on the building side and in the boreholes. Inlet and outlet temperatures are measured every thirty seconds with a specific datalogger. The test bench was designed to consume the less possible energy: the heat extracted at the building side is used to heat up the boreholes side. Two hydraulic separators on the building side and on the borehole side allow the heat pump flowrate to be independent from the bench flowrate. The pressures losses of the heat pump circulators can thus be adjusted to correspond to real floor heating and boreholes.

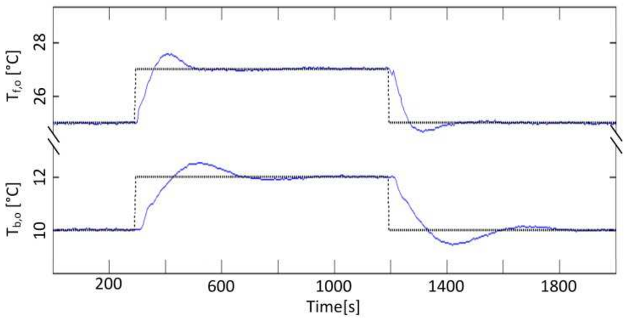

Figure 3: Test-bench response to setpoint step changes.

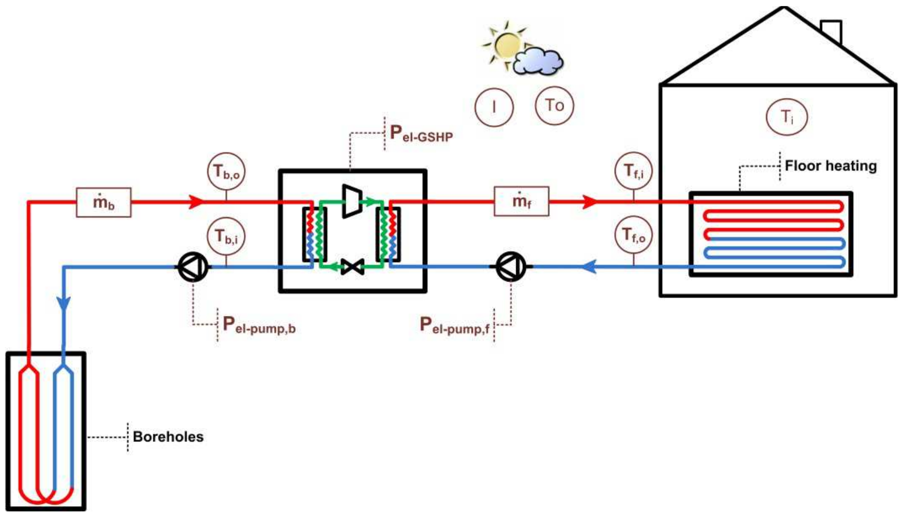

Figure 4 : In-situ monitoring of a GSHP system on a dwelling in Marck (France).

III. CALIBRATION OF SIMULATED PART

A. *In-situ measurements*

A single family-house located in Marck (France) has been monitored during the 2011/2012 heating period. The dwelling is conform to the 2005 French regulation (RT2005) and has the following characteristics:

- Surface area of 100 m^2.
- External walls: brick (11 cm), air layer, cellular concrete (11 cm), glass-wool (10 cm), air layer, plasterboard (1.3 cm). Global U-value of 0.18 W.m-2.K-1 ;
- Double glazing, U-value of 1.5 W.m-2.K-1 ;
- Windows distribution: North 7%, South 10%, East 17%, West 0% ;
- Single flow hygro-adjustable ventilation ;
- Equipped with a 8.5 kW GSHP connected to a floor heating;
- Double U-pipe vertical boreholes of 100m depth.

The renewable energy monitoring box (REMBO) developed by the CSTB acquires, treats and sends measured data every minute to a server. Flow rates and temperatures on the building side and on the borehole side are measured as well as electric consumptions of compressor and pumps. Outside and room temperature are also measured. Global horizontal solar radiation is obtained from satellite images thanks to the SODA service [10].

B. *Modeling of the GSHP system*

The whole system model is based on Matlab/Simulink environment using the SIMBAD toolbox (Simbad, 2004). The system includes the following components (

Figure 5):

- Building part (building, floor heating system, occupants, ventilation and equipment);
- GSHP;
- Borehole heat exchanger part.

The building was modeled with the Simbad multizone model [11] and designed with the associated SimBDI graphical interface. A simple monozone model has been chosen.

The floor heating model developed by Salque [12] is based on finite difference method. It consists in a 2D-grid of the slab coupled to a pipe model. The floor heating is made of four layers (floor covers, slab with pipes, insulation and concrete floor) with different thermal properties.

The heat pump model is based on experimental data. The coefficient of performance (COP), which is the ratio of the heat produced at the condenser to the electric energy consumed by the compressor, is determined with the method of least squares for a plane equation, depending of average temperatures at both condenser and evaporator side.

The boreholes model developed by Partenay [13] is based on finite difference method. It consists in a 3D-grid of the ground coupled to a pipe model, allowing the modeling of single or double U pipes. The heat conduction problem is solved with a state-space formulation.

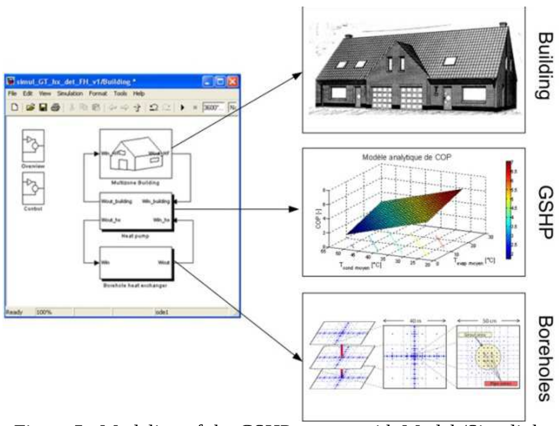

Figure 5 : Modeling of the GSHP system with Matlab/Simulink.

C. Fitting of simulated part

The objective is to fit the simulated GSHP system to the measured data to obtain a realistic simulation environment. The system components parameters (boreholes, GSHP, floor heating and building) are identified separately. For each component, the physical parameters known a priori were fixed, while others were fitted by least square minimization. A step by step method for tuning the physical parameters of the different models was proposed by Salque [12]. A specific iterative process for parameters identification of building and floor heating was developed since these components are physically coupled. An overview of this method is detailed here, for more information please refer to [12].

- Boreholes parameters identification

Design parameters such as the radius of drilling, borehole length or pipe diameter are fixed since they are known from in-situ measurements. Modeling parameters such as the radius of domain and the number of nodes are also fixed to simplify the problem. The unknowns concern the thermal characteristics of the ground (ground conductivity and heat capacity) and the initial ground temperature. These variable parameters were adjusted in a physical range of values to best fit the measured data. The following values were found to be the optimal set of parameters:

- Ground conductivity : 2.2 W/(m.K)
- Ground heat capacity: 2180 kJ/(kg.K)
- Initial ground temperature : 12.2°C

The Root Mean Square (RMS) error on outlet temperature with the optimal set of parameter is 0.41°C. The error in terms of energy extracted from the ground during the month of March is lower than 1%.

- Floor heating and building parameters identification

The building was modeled with the Simbad multizone model [11] and designed with the associated SimBDI graphical interface. Geometry and wall compositions of the identified dwelling were read from plans. Due to a large number of unknowns related to the occupants' behavior (windows opening, internal gains, etc.) and the exact location of the room temperature sensor, a simple monozone model has been chosen. Design parameters such as building geometry, wall composition or floor heating surface are supposed to be perfectly known and fixed. The real hygro-adjustable ventilation is modeled by simple-flux ventilation with a constant air flow as humidity ratio of indoor air is unknown.

Since internal gains and ventilation parameters compensate when trying to fit the building model, internal gains were fixed to a typical value while the ventilation rate was estimated. A constant blinds position between 0 (closed) and 1 (open) was also estimated to fit the solar gains. The composition of floor heating layers is known in a range of uncertainty. It was found that the adjustment of the most influent layer (slab with pipes) is enough to make the model fit. Another crucial floor heating parameter that needs to be adjusted is the pipe spacing that is proportional to the heat-exchange surface between fluid and floor heating

Since there are no measurements of surface temperature, the identification of both floor heating and building models has to be made in parallel. The optimal set of parameters was found to be:

- Pipe spacing : 0.33 m ;
- Floor heating conductivity : 1.9 W/(m.K) ;
- Floor heating inertia : 8950 kJ/K ;
- Ventilation rate : 0.36 vol/h;
- Blinds position: 0.8 [-].

- GSHP parameters identification

The GSHP model is only required to verify that the global simulation still fits the measured data. The heat pump COP is modeled by the following function, developed by Partenay [13]:

$$COP = a * T_{evap} + b * T_{cond} \tag{1}$$

where T_{evap} and T_{cond} are the average temperatures at evaporator and condenser side. For a given temperature level in the heating floor, COP behaves as a linear function of the temperature level in the ground. Experimental tests revealed that electric power Pel was only a function of condenser temperature. The chosen model is expressed as follows:

$$P_{el} = d * T_{cond}{}^{2} - e * T_{cond} + f \tag{2}$$

The coefficients *a, b, c, d, e, f* are identified using the least squares method (*a*=5.09, *b*=0.16, *c*=-0.05, *d*=-81.9, *e*=66.9, *f*=-0.55).

- Global simulation results

The identified models are now integrated in a global simulation in Matlab/Simulink. The month of March is simulated and compared to the measured data. The measured heat pump on/off control is applied to the simulated heat pump. This way the differences between simulation and measurements are only due to the modeling and cannot be attributed to an incorrect estimate of control logic. Besides, the action of the occupants on room temperature setpoint makes it very difficult to accurately estimate the control logic.

Figure 6 shows the comparison between simulated and real GSHP system. The first graph on top shows simulated and measured room temperatures. The identification of the thermal behavior of the building is satisfactory. Indeed, simulated and measured room temperature extremum are in phase. The RMS error on room temperature over the whole month is 0.63 °C. The RMS error is 26 W for condenser power and 18 W for evaporator power. Simulated heating energy consumption is 558 kWh while measured consumption is 541 kWh.

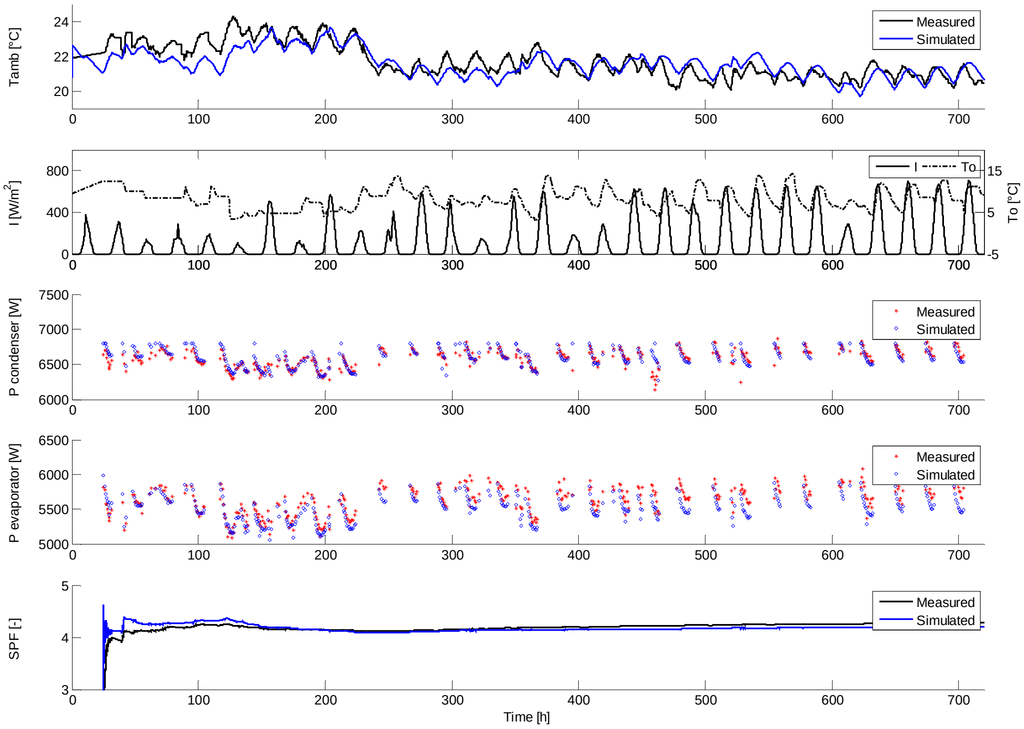

Figure 6 : Comparison of global simulation results and in-situ measurements – Month of March.

The last graph shows the SPF, which is the ratio between heating energy delivered to the building and electric energy consumed by the compressor. The SPF over the month of March obtained by simulation is 4.28, while the real SPF is 4.21.

IV. THE PREDICTIVE 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.

A. Controller strucutre

The modular structure of the controller is illustrated in Figure 7. 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. Based on these predictions, another ANN makes predictions of room temperature T_i. The optimization block determines the optimal trajectory to be applied to the system according to the various trajectories of T_i and P_{el}.

B. Control strategy

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

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

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

where $\widehat{T}_i(k)$ 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.

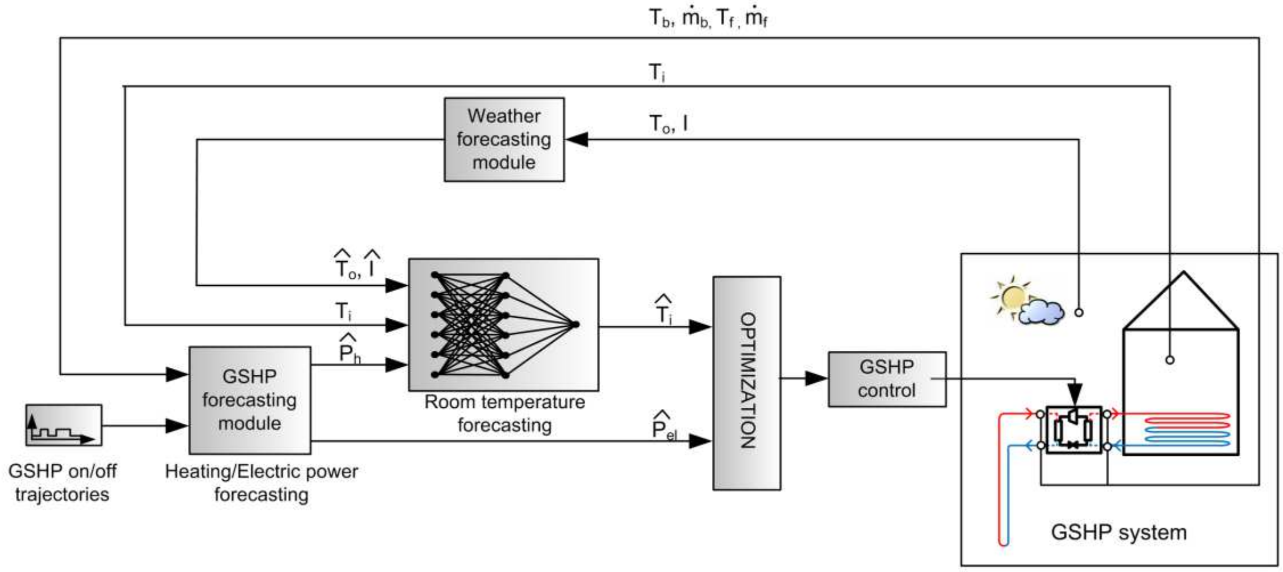

Figure 7: Flow chart of the ANN-based predictive controller. The symbol (^) is assigned to the predicted values.

C. 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 [14]. 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 hours receding horizon is applied and the optimal control problem is repeated every 15 minutes.

D. 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 [15].

E. ANNs training process

The various modules were first optimized via extensive off-line tests conducted with the neural network toolbox in Matlab [16]. The objective is to produce a network that fits the data as accurately as possible, but simple enough to train easily and generalize well. Optimization is an iterative process that consists in finding the ideal ANN structure, algorithm and set of input variables.

The ANNs architecture is a multilayer perceptron. 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 [17] and then optimized by trial-and-error until no improvement could be seen.

Another key step in the process of ANN building is the choice of inputs and associated time delays. For nonlinear models such as ANN, there is no systematic approach [18] 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. The model has to be as simple as possible while taking into account the most relevant inputs. Again, optimal sets of inputs and time delays are obtained by trial-and-error. A hyperbolic tangent sigmoid function was used as the transfer function in the single hidden layer. 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. With 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 ANNs but does not interfere during the training process.

For online applications, ANNs have to be trained regularly on new data set to adapt to changes in the system. For instance, during the heating season, the boreholes temperature will fall. To take into account this phenomenon, studies not presented here showed that the ANN for borehole temperature prediction has to be trained every 15 days on the last 30 days data.

F. Room temperature prediction

ANN for room temperature prediction is here detailed as this module is of most interest. For more information on the other ANN modules, please refer to [19].

- *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.

- *Optimal structure*

The developed ANN provides room temperature T_i for the next time step from current weather data (T_o, I) as well as previous and current values of heating power P_h and room temperature T_i. This ANN making the link between the heating power delivered to the radiant floor and the impact on room temperature, it encapsulates both the thermal behavior of the building and the emitter. In particular, the thermal lag of the radiant floor is taken into account in the ANN using P_h(k-1). A wide range of current and previous values of these variables was tested as inputs. The optimal ANN structure and set of inputs for room temperature prediction of the studied building are presented in Figure 8.

Offline tests revealed that the mean value of the outdoor temperature on the last 24 hours $\overline{To_{24}}(k)$ contains enough information to describe the dynamic behavior of the tested building. For less insulated buildings or buildings with a higher ventilation rate, the impact of the outdoor temperature is higher and the current value of T_o is likely to be more appropriate. The ANN used in this module has 6 input neurons, one hidden layer of 6 neurons and one output neuron.

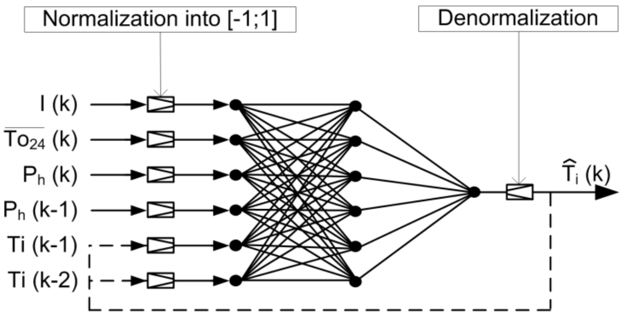

Figure 8: ANN architecture for room temperature prediction.

- *Comparison with ARX model*

ANN performances for room temperature prediction are compared to linear ARX models, which are commonly used for the building model in predictive control. ARX models are Auto Regressive models with eXternal inputs that can be written as follows:

$$\begin{aligned} y(t) &= B * [u(t-1), u(t-2) \dots] \\ &+ A * [y(t-1), y(t-2) \dots] + A * \varepsilon(t) \end{aligned} \quad (5)$$

where $y(t)$ is the output vector, $u(t)$ the input vector and $\varepsilon(t)$ a white noise with zero mean.

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. 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 over the 6 hours prediction horizon. The main results are summarized below:

- 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 do not give accurate results.
- 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 inertia of the building and the floor heating.
- Taking into account previous values further into the past does not improve the prediction performances of both types of models.

An example of 3 hours prediction results of ANN3 and ARX3 models on a representative week of March is given in Figure 9. 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 9).

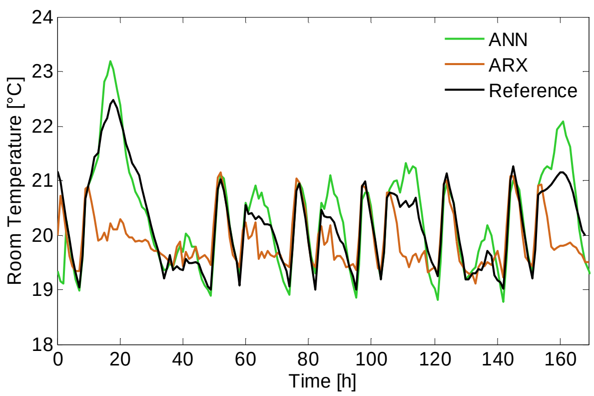

Figure 9: 3 hours prediction of room temperature.

V. Comparison of Controllers on the Semi-Virtual Test Bench

A. Conventional controller

For the test, the real measured controller output is used as a reference. This on/off signal is applied to the heat pump connected to the bench. It can be noticed that the heat pump installed in the laboratory is the same heat pump of that in the monitored dwelling. This reference controller is a Compensated-Open-Loop (COL) controller that is installed by default with most single-speed GSHP systems. The COL controller is based on the following heating curve that is adjusted with the actual value of room temperature:

$$T_{HC} = (a * T_o + b) - c * (T_i - T_r) \quad (6)$$

where T_o is the outdoor temperature and $(T_i - T_r)$ the difference between the actual and the setpoint room temperature. The coefficients a and b are the heating curve parameters while c is the ambient compensation factor. The COL controller switches on/off the GSHP when the water supply temperature $T_{f,s}$ is beyond T_{HC} ±2°C. This control logic requires the pump on the building side to always be working to keep the fluid circulating. The COL controller is represented in Figure 10.

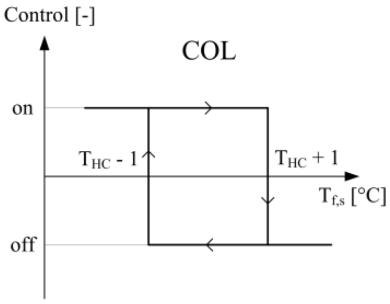

Figure 10 : Control logic of the COL conventional controller.

B. Experiment process

- *Test procedure*

The ANN controller is compared to the COL controller during two sequential tests of one week on the bench. The complete test procedure is illustrated in Figure 11. The procedure starts with an initialization phase from February 15th to March 15th that consists in a simulation of the whole system. During this phase, the measured on/off signal is applied to the simulated heat pump. Initialization period is also required to train the ANN modules of the predictive controller: the training data set is from February 15th to February 28th while the validation data set is from February 29th to March 15th. At the end of the initialization, the real-time testing of the controller starts. The simulated building and boreholes are in the same thermal state at the beginning of each test to ensure an accurate comparison.

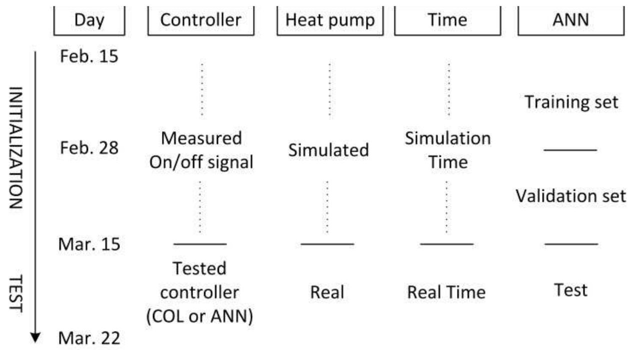

Figure 11 : Procedure of the semi-virtual test of the controllers.

Since the real GSHP has a very small time constant (the steady-state of the heat pump is almost immediately reached), the real-time testing can in fact be accelerated to significantly reduce the duration of the test. The acceleration factor of real-time depends on the minimum duration of a compressor cycle during the test as well as the response time of the bench. In our case, the bench approximately takes 3 minutes to reach the setpoint ± 0.5°C when the compressor starts. With the ANN controller, the minimum duration of a compressor cycle is 15 minutes (time lapse between 2 controller's calls). With the conventional controller, in-situ measurements showed a minimum of 12 minutes per cycle. Based on these durations, the real time has been accelerated by 2 to ensure the bench to accurately control the temperatures.

- *Heat pump control*

The heat pump is controlled via programmable resistances that replace the heat pump outdoor and room temperature sensors. An outdoor temperature drop activates the heat pump compressor, and vice versa. This way the control of the heat pump is non-intrusive.

C. Controllers' performances comparison

Room temperature setpoint of ANN controller is set to 22.5°C with a comfort parameter $\Delta T_{max} = 0.5°C$. This temperature corresponds to the mean room temperature observed with the conventional COL controller.

A comparison of the controllers on the test week is depicted in Figure 12. COL controller leads to small room temperature overshoots in the afternoon. It can be noticed that when the GSHP is switched on in the morning of a sunny day, the dwelling is likely to be overheated in the afternoon. This is of course due to the fact that the conventional control logic does not integrate a prediction of solar gains.

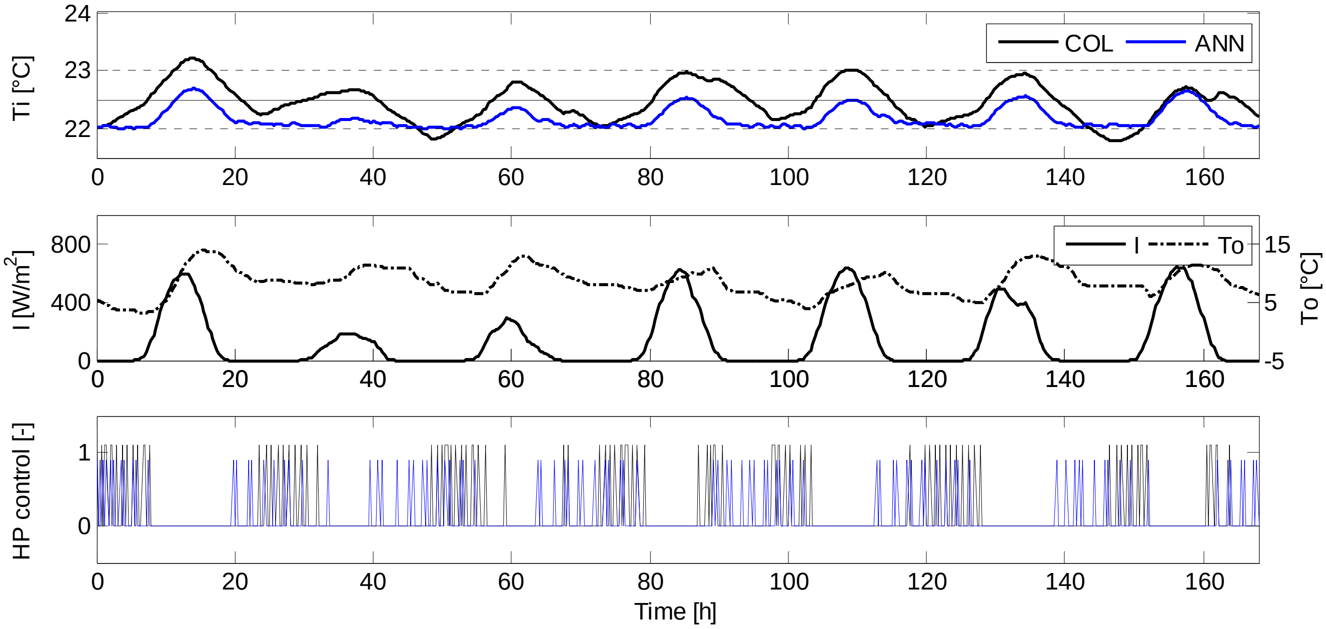

Figure 12 : Comparison of the controllers over the test week. % 15-22 March.

ANN controller keeps room temperature in the comfort range thanks to its prediction capability. Room temperature is lowered just before solar gains are expected so that to avoid overheating and benefit from free heat gains, leading to energy savings. Heating loads are thus shifted to anticipate solar gains.

Results in terms of energy consumed and heat pump performances over the test week are presented in Figure 13. Thermal energy delivered to the floor heating is 152 kWh with COL and 147 kWh with ANN, i.e., a gain of 3%. Total electric energy consumed by the GSHP system is 60 kWh with COL whereas ANN controller only consumes 36 kWh. This gain of 40% in energy consumption is mainly due to the fact that the pump on the floor heating side is constantly running with COL.

Heat pump efficiency is expressed here as a Seasonal Performance Factor (SPF), which is the ratio between the energy delivered by the heat pump and the electrical energy consumed by the compressor or by the compressor and the pumps (global SPF). The compressor SPFs are almost identical with both controllers. The ANN compressor SPF is slightly higher (4.6) than COL (4.5) as mean duration of compressor cycles is lower with ANN. Longer cycles indeed lead to higher temperatures in the floor heating and thus a lower heat pump efficiency. Global SPF with COL is only 2.5 because of the high consumption of the pump on the building side, while global SPF with ANN is 3.9.

VI. CONCLUSION

For the purpose of comparing different controllers sequentially and under identical conditions, a test procedure has been developed on a calibrated semi-virtual test bench. A real GSHP has been connected to the test bench that emulates the building and the boreholes.

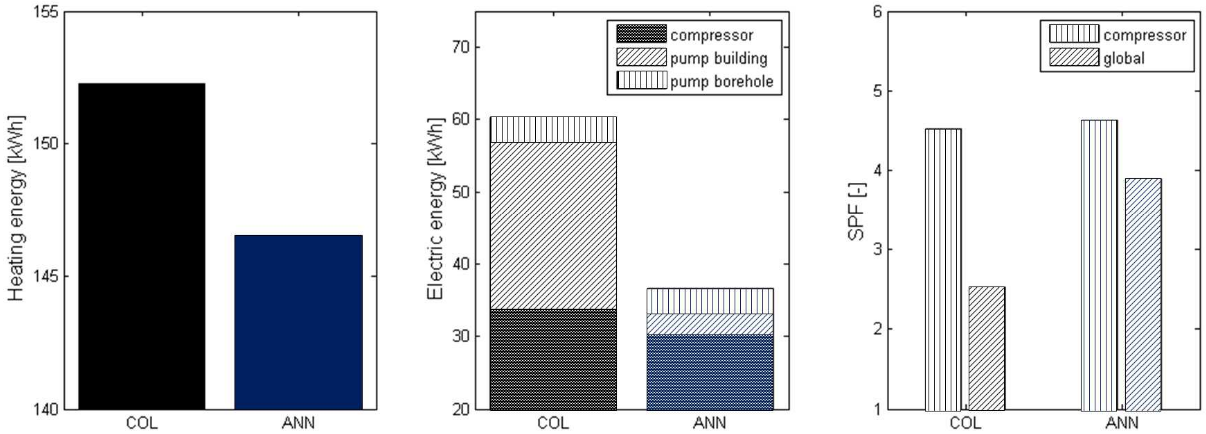

Figure 13 : Test results in terms of energy consumption and heat pump efficiency SPF% over the testing week.

The controllers' tests can thus be carried out under dynamic conditions: dynamic weather conditions are used as input of a building simulation including floor heating and boreholes. The simulation environment has been designed to reproduce all characteristics (building, weather, boreholes, etc.) of an in-situ GSHP that was monitored during the 2011/2012 heating season in the north of France. This way the tests were carried out under realistic and reproducible conditions, which is practically impossible with sequential in-situ tests. Another advantage of the semi-virtual test-bench is that the real time of the test can be accelerated to significantly reduce the duration of the test (3.5 days instead of 7 days).

The developed ANN predictive controller for single-speed GSHP has been detailed including the training process, the determination of optimal input data, algorithm and structure.

The ANN controller has been compared to the COL conventional controller during two sequential tests of one week on the bench. The ANN controller allows an energy gain of 40%, mainly due to the fact that the pump on the floor heating side has to be constantly running with COL. This also results in a better global SPF with ANN.

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