AUTOMATED CALIBRATION OF AIR HANDLING UNIT MODELS USING A MODIFIED PREISACH MODEL

Jesús Febres, Raymond Sterling, Marcus Keane
Informatics Research Unit for Sustainable Engineering, IRUSE, National University of Ireland Galway, NUIG, Galway, Ireland

ABSTRACT

This paper presents a new approach to calibrate air handling unit models. This approach studies every heat exchanger component separately based on the inverse problem framework, the Preisach model of hysteresis and machine learning techniques. For each component model, the first step is to solve the inverse problem in order to calculate the optimal control signal that generates the output values expected from real data. Then, a modified Preisach model is calibrated using machine learning techniques where the input-output pair samples correspond to the actual control signal taken from the real data and the optimal values obtained from the previous step. The last step is coupling both the first principle based model of the heat exchanger and the calibrated Preisach model.

A detailed case study is presented.

INTRODUCTION

Nowadays, optimisation of heating, ventilation and air conditioning (HVAC) systems operation has become an active research field due to the demanding energy efficiency goals in buildings (European Parlament and Council of the European 2010). Therefore, recent developments in modelling and simulation methodologies and software enable HVAC models simulation to support buildings operation. This provides a reliable test bed on which engineers can carry experiments avoiding the risks associated with doing them on the physical system. Although modelling approaches seem to be converging to a structured framework depending on the particular application, the calibration of HVAC models remains an open research area.

The calibration process can be divided in two key parts, the calibration methodology *per se* and the validation of the calibration results using the appropriate metrics. This research work focuses on the development of a novel automated calibration methodology for HVAC components and its implementation.

THE MODELS

This paper studies air-handling units (AHU) with constant air volume and their typical components, i.e. mixing box, cooling coil, heating coil and humidifier. As in some grey box approaches, each component's model consists of two sub-models: a white-box (WB) that takes into account prior knowledge of the physical behaviour of system (e.g. first principle equations defining the interactions between elements); and a black-box (BB) that models the input-output relationships without any physical interpretation. The heat exchanger (HX) model –based on first principles– represents the WB, and the control element –based on the Preisach model of hysteresis– corresponds to the BB.

Figure 1 shows the division in two sub-model of the heating/cooling coil model.

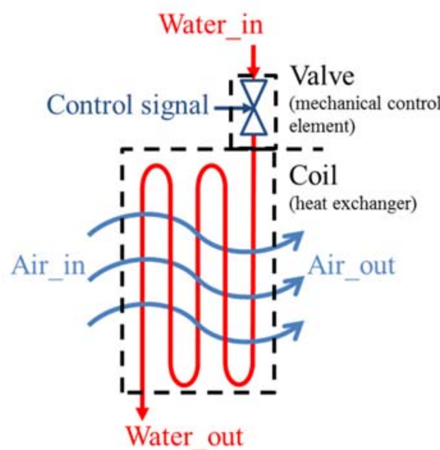

Figure 1. Heating/cooling coil example

Heat exchanger models

Usually, an AHU comprises a combination of the following components: mixing box (MB), cooling and dehumidification coil (CC), heating coil (HC), humidifier (H), ducts, filters, fans, temperature sensors (T), relative humidity sensors (RH), air velocity sensors (AV) and actuators (%), as shown in Figure 2. The focus of this research work is the so-called active elements used for changing the air temperature in the AHU, i.e. MB, CC and HC. They are briefly described in this section, however, a more detailed description was presented in (Febres et al. 2013).

The following assumptions are considered:

- Ducts and filters have negligible effects on air temperature;

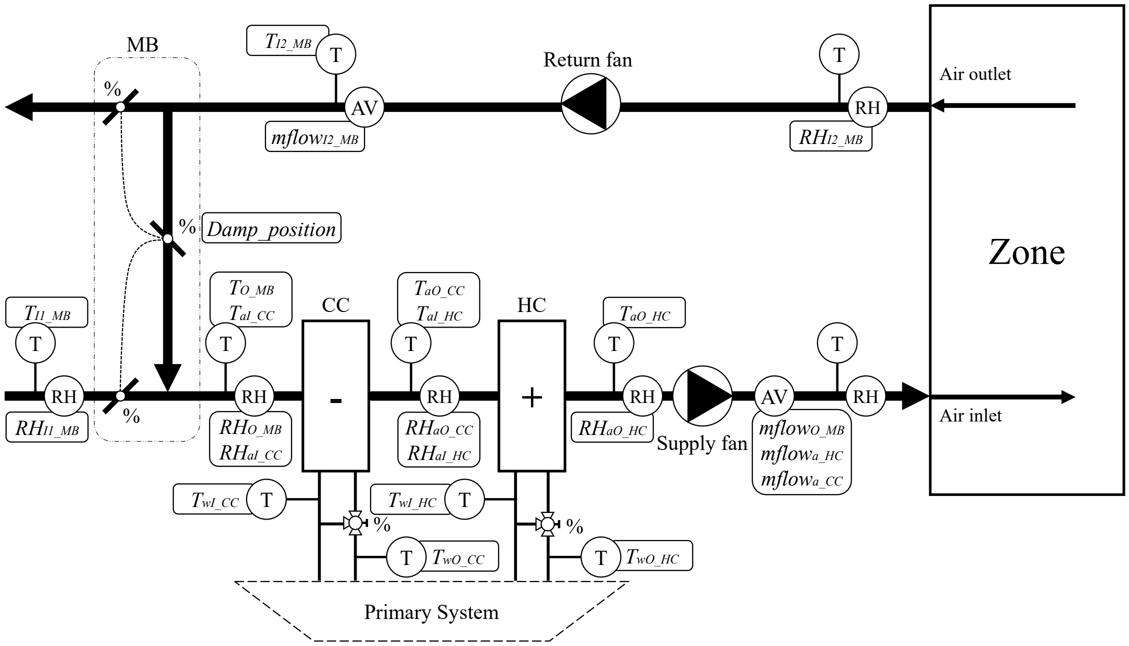

Figure 2. Air handling unit schematic

- Fans cause a constant air temperature increment and has no effect on the air humidity ratio;
- The humidifier causes a negligible air temperature increment and has effect just on the air humidity ratio;
- Both air and water are incompressible ;
- Steady and adiabatic conditions.

The **mixing box component** is modelled using Eq. 1 to Eq. 5 (Tashtoush et al. 2005). They describe the energy and mass balance between the mixing air streams.

To calculate the mass flow rate of the air outlet it is used a simple mass balance equation:

$$mflow_O = mflow_1 + mflow_2 \qquad Eq.\ 1$$

The mass flow rate variables, $mflow_1$ and $mflow_2$, are defined by:

$$mflow_1 = mflow_{I1} * damp\_position \qquad Eq.\ 2$$

$$mflow_2 = mflow_{I2} * (1-damp\_position) \qquad Eq.\ 3$$

where *damp_position* is the control signal.

Finally, the output temperature and humidity ratio are computed using the following energy balance equations:

$$mflow_{I1} * T_{I1} + mflow_{I2} * T_{I2} = mflow_O * T_O \qquad Eq.\ 4$$

$$mflow_{I1} * W_{I1} + mflow_{I2} * W_{I2} = mflow_O * W_O \qquad Eq.\ 5$$

The **heating coil** model is derived from (ASHRAE 2009). It calculates the outlet steady-state conditions in both, water and air sides, using equations derived from the principles of energy and mass conservation and the definition of heat transfer effectiveness in the classical eff-NTU method given by:

$$Q = C_a * (T_{aO} - T_{aI}) \qquad Eq.\ 6$$

$$Q = C_w * (T_{wO} - T_{wI}) \qquad Eq.\ 7$$

$$Q = eff * \min(C_a, C_w) * (T_{wI} - T_{aI}) \qquad Eq.\ 8$$

The effectiveness *eff* equation depends on the coil configuration, i.e. parallel flow, counter flow or cross flow with both streams unmixed.

The **cooling/dehumidifier coil** model is based on dry/wet model presented in (Lemort 2008). It computes two operation regimes, fully dry and fully wet. Initially, the model calculates the cooling capacity for both regimes, and then the regime with the lowest capacity is discarded while the regime with highest capacity is chosen as the actual regime for further energy calculations.

In dry regime, the outlet steady-state conditions in both sides (water and air) are calculated using the heating coil model previously presented. Wet regime model uses the same equations, but the wet-bulb air temperature substitutes the air temperature variable. This approach is based on the assumption that the air is a perfect gas, thus its enthalpy is fully defined by the wet bulb temperature. In addition, the variables C_a and *eff* from Eq. 6 and Eq. 8 are calculated assuming the coil is a semi-isothermal heat exchanger.

Control element model

Typically, actuators such as valves or dampers control the components under study. They represent the **control element**, which is often characterised as a non-linear element showing hysteresis behaviour. A suitable representation of the hysteresis is provided by the Preisach model of hysteresis in its discrete version (Tan et al. 2001). This hysteresis model can be seen as a linear combination of the nonlinear functions (named hysterons) as shown in Figure 3. In addition, by fixing the defining parameters of the hysteron function (α and β in Figure 3), the Preisach model can be considered as a **linear neural network** (LNN) where each hysteron is a neuron and the coefficients are the weights of the network. In this way, machine learning techniques can be used to automate the calibration process of the valve or damper model.

THE METHODOLOGY

Figure 4 shows a general overview of the whole procedure including development of the models for both, heat exchangers and control elements, and the automated calibration process. First, the theoretical models have to be formulated for both, the heat exchanger and the valve. Second, the formulated models need to be implemented in the form of computational models (step 1 in figure). Third, a pre-calibration process for the coils is performed (step 2 in figure). Finally, the fine calibration is completed in steps 3 to 5.

Data collection

In order to use the proposed methodology, two sources of data are required. First, the heat exchanger pre-calibration process needs the manufacturer data-sheets in step 2. Second, step 4 requires operational data from the data-collecting framework (normally the BMS) in order to carry out the control element calibration.

Model formulation

As mentioned, the heat exchanger model is based on first principles, i.e. mass and energy balance equations while the control element model is an adaptation of Preisach hysteresis model in its discrete version incorporating LNN concepts.

Step 1. Models implementation

Once the theoretical models are formulated, both heat exchanger and control element (named as HX_Mo and H_Py in Figure 4, respectively) have to be implemented in some computational language. In this research work, the former was implemented in Modelica, which is a programming language specialised in first principle based models modelling. The later was coded using Python due to its data-processing capabilities particularly suitable for machine learning applications.

Step 2. Heat exchanger pre-calibration

The heating and cooling coils require a pre-calibration. They need initial parameter values in order to run, i.e. a minimal data set is required. Opportunely, the manufacturer's data sheet provides the required information, which is used as model parameters in the Modelica models (Pre_HX in Figure 4).

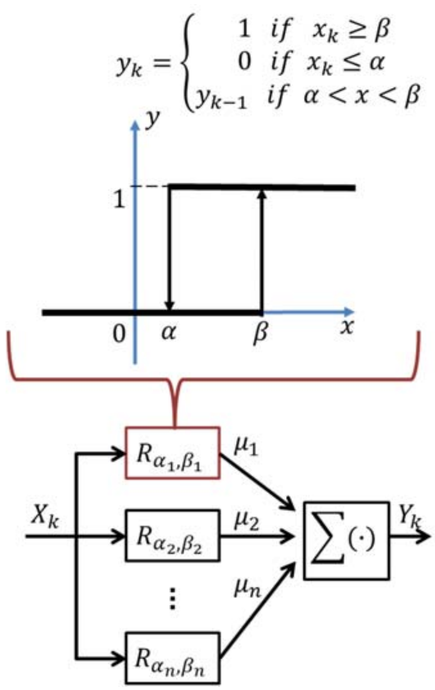

Figure 3. Discrete Preisach model of hysteresis. Top: discrete relay hysteron $R_{\alpha,\beta}$. Bottom: linear combination of a finite number of hysterons

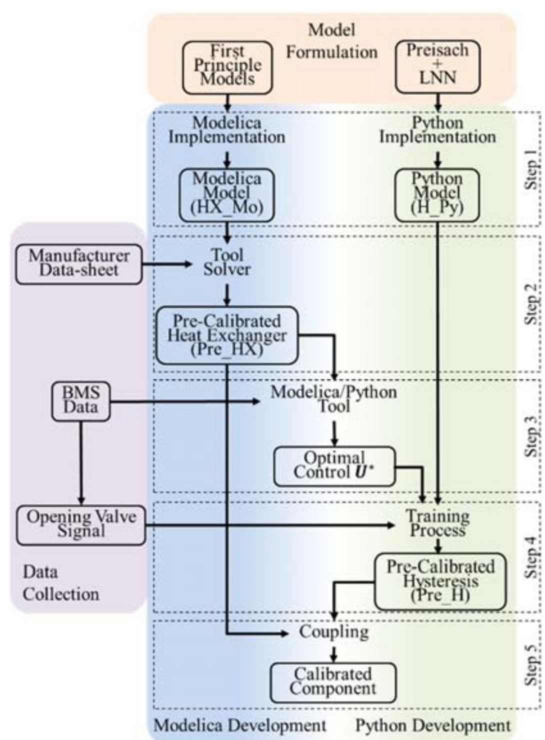

Figure 4. Proposed Methodology

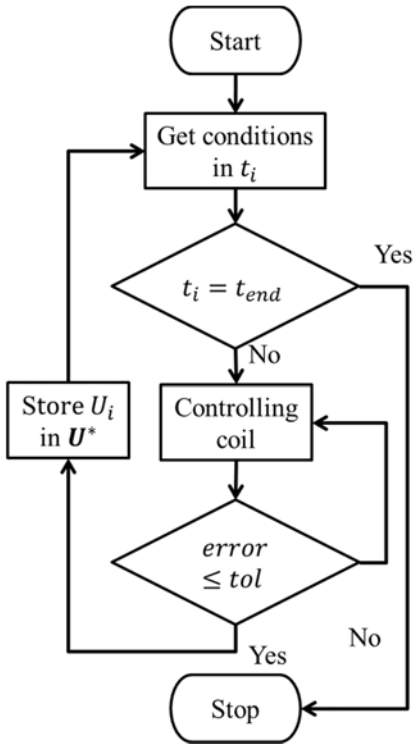

Figure 5. Optimal control signal computation

Step 3. Optimal control signal computation

In order to calibrate the control element model, it is first necessary to find the optimal values for the control variables. Those values are so that the difference between simulated and measured output variables remains within a fixed tolerance for every sample taken from the calibration data set. In other words, getting the optimal values is equivalent to solving the inverse problem for the heat exchanger model (find the inputs given the outputs). Table 1 shows the corresponding control and output variables for the components under study.

Table 1. Control and output variables for each component

Component	Control variable	Output variable
Mixing box	Damper position	Outlet air temperature
Heating/cooling coil	Water mass flow rate	Outlet air temperature
Humidifier	Steam mass flow rate	Outlet air humidity

In some cases, Modelica tools can solve the inverse problem. However, this is not necessarily possible in models that include a high non-linearity, e.g. where complex combinations of if-then-else statements are used.

To provide a generic solution, this paper proposes to consider the problem as a discrete control problem. Consider the control system in Figure 6:

- The plant P is the heat exchanger (white-box) model;
- The signal U is the corresponding control variable;
- The controlled variable Y is the output variable from the component model;
- The reference signal R is the measured (and expected) value of the output variable from calibration data.

The idea is to find U so the error is within a fixed tolerance ε for each value of R taken from the calibration data set.

This process corresponds with step 3 in Figure 4 where the resulting values of U are stored as $\boldsymbol{U}^*$.

Finding U requires an iterative procedure depicted in Figure 5 and summarized as follows:

1. $\boldsymbol{U}^*$ is initialized as an empty vector with length equal to the number of samples used for the model calibration;
2. One sample from the calibration data set is taken and used as the reference signal R for controlling the process until the error between Y and R is below the tolerance;
3. Once this happens, the current value of the control signal U is stored in $\boldsymbol{U}^*$;
4. Repeat steps 2 and 3 until for every sample in the ser.

Although the pre-calibrated model was implemented

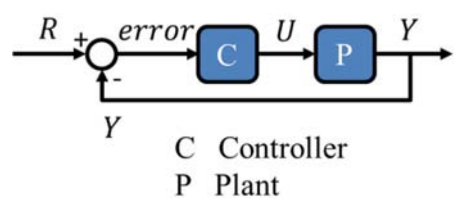

Figure 6. Control system diagram

using Modelica, the process described above was coded in Python using a Python/Modelica middleware developed for co-simulation purposes presented in (Febres et al. 2014). Since the process involves the use of both, Python and Modelica, this task is in between Modelica development and Python development in Figure 4.

Step 4. Control element calibration

As previously stated, the control element model is based on the Preisach model of hysteresis and machine learning concepts. For this research work, the control element calibration process was performed using a supervised learning approach, more in particular using linear least squares and its normal equations (Orr 1996). The training set is defined by input-output pair values of $\boldsymbol{O}$ and $\boldsymbol{U}^*$, where $\boldsymbol{O}$ is the control signal

(Table 2) taken from the BMS calibration data set and ***U**** is the optimal control signal found in step 3.

Table 2. Control signal from data set for each component

Component	Control signal
Mixing box	Damper opening
Heating/cooling coil	Valve position
Humidifier	Valve position

Step 5. Model coupling

The final step in the model calibration process consists in coupling both, the pre-calibrated heat exchanger model and the calibrated control element model. Since the HX model is implemented in Modelica and the control element model in Python, the final coupling is performed making use of the same Python/Modelica interface used in step 3.

CASE STUDY

The case study is the air-handling unit (AHU) depicted in Figure 2. The AHU serves a facility consistent of an audio laboratory of around 50 m2, where strict conditions of temperature and humidity must be met. The building is located in the city of Cork in the Republic of Ireland.

The unit under study is a reasonably well instrumented AHU making it suitable for research purposes. The available sensors can be seen in Figure 2, where 'T' stands for temperature sensor; 'RH' for relative humidity sensor, 'AV' for air volumetric flow rate sensor and '%' represents the opening of valves and dampers. The signals and sensors data is recorded by the building management system (BMS) with a frequency of one minute per sample.

All simulations were performed using a personal computer with a 2.8 GHz dual-core processor and 8 GB in RAM. Dymola 2013 FD01 (64-bit) as Modelica IDE and Python 2.7 were used in this paper.

Data collection and pre-processing

In order to capture the hysteresis behaviour of the control element, experiments were set up spanning the whole range of possible control variable values

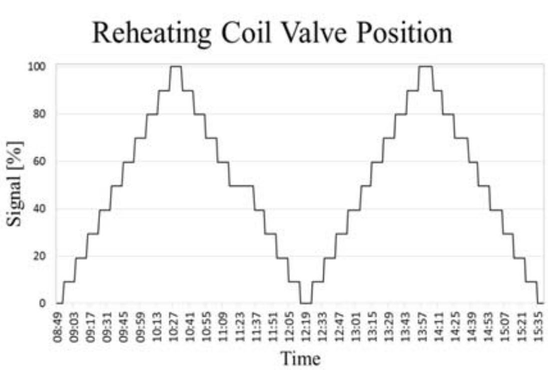

Figure 7. Typical controlling variable signal behaviour during experiments

(valves and damper position). Starting at the completely closed position, the valve (or damper) is incrementally open in steps of 10% every 10 minutes. Once it is completely open, the control signal is decreased at the same rate, i.e. 10% every 10 minutes. The spanning process finishes when the valve (or damper) is completely closed once again. This process was performed twice for each component (Figure 7).

Since the models are based on steady-state equations, the calibration data had to be filtered. A moving window steady-state detector was used for this task. This algorithm uses the standard deviation of the moving window in order to detect system steady-state and calculates it in a recursive fashion (Kim et al. 2008).

Models implementation

For the implementation of the control element model, the input space of the valve and damper (i.e. [0,1]) was discretized into 50 partitions of equal lengths (i.e. steps of 0.02). In the neural network implementation of the control element (see Figure 3), a neuron is created per each possible (α, β) pair. By partitioning the input space in 50, the resulting number of neurons (hysterons or relays) is given by the combination $\left(\binom{50}{2}\right)$ resulting in 1275 relay units. To this, a bias unit is added as it isstandard practice in neural networks for a total neuron count of 1276. The number of partitions was selected as a trade-off between expected accuracy and computational resources needed to train the neural network.

For the implementation of the component models, manufacturer information and physical quantities used as parameters for each component are presented in Table 4

Optimal control signal computation

A tolerance $\mathcal{E}$ of 0.1%, of the expected value Y , in the error between R and Y was defined in order to find ***U****.

The optimisation process was carried out iteratively by using the bisection method.

To avoid any inconsistency in the calibration data, only the working hours of the unit were taken into account during this process. Hence, the calibration was done using samples where the fan was turn on, i.e. the air flow rate was greater than or equal to 1.0 m^3/s.

Control element calibration

The model was trained using an active set algorithm to solve the non-negative linear least square problem (Lawson & Hanson 1995).

Figure 9 shows the resulting hysteresis for each component after calibration. Different aspects can be noticed in the graphs. The actual opening of the loop, the point where the signal starts to increase, the point where it stops increasing, etc. It is clear how these plots can provide a limited but useful information about health status of the control elements. For example, on the top graph, the mixing box damper presents a very wide loop which, usually, is a sign of malfunctioning due to damper wear. Also, from the

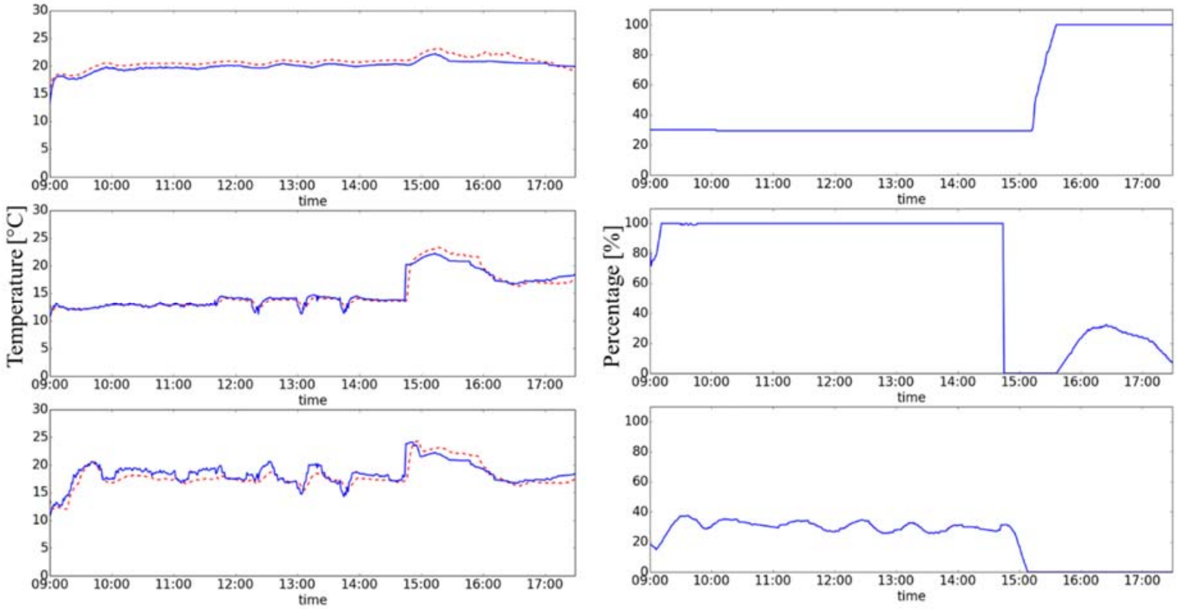

Figure 8. Left hand side: output temperature (simulated and measured). Right hand side: control signal. From top to bottom: mixing box, cooling coil and heating coil

middle graph, the output of the cooling coil valve gets a constant value over 50% which could be interpreted as the valve gets stuck for opening signal values higher than 50%. These points will be further explored in future works.

Model coupling and validation

The resulting calibrated models of each component, from steps 2 and 4, were coupled using the Python/Modelica interface. Then, the whole AHU model was assembled using the calibrated/coupled models of each component.

The calibrated AHU was simulated using validation data sets. The simulated and measured outlet air temperatures for each component corresponding to one day of the validation set are presented in Figure 8 (left hand side). The figure also shows the control signals from the BMS (right hand side).

Two of the most common metrics used to qualify the goodness of the calibration processes are the coefficient of variation of the root-mean-square error (CV-RMSE) and the normalised mean bias error (NMBE) (ASHRAE 2002). However, in this research work, the variables under study are temperatures in Celsius scale. This scale is an interval scale that should not be used to calculate those types of errors since it requires non-negative values to guarantee an average above zero. To avoid this inconvenient, the chosen metric was the normalised root-mean-square error NRMSE since it is normalised using a positive difference.

Table 3 shows the NRMSE of the output temperature for each component. Those errors are calculated after assembling all components.

Results show that the deviation of the output in the cooling coil is compensating the error from the mixing

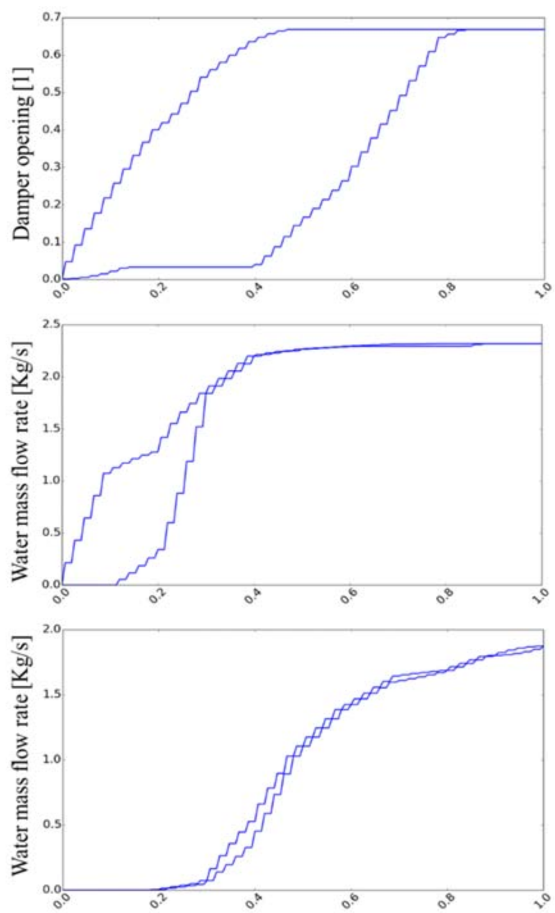

Figure 9. Hysteresis behaviour. Top: Mixing box, damper opening vs opening signal. Middle: Cooling coil, water flow rate vs opening signal. Bottom: Heating coil, water flow rate vs opening signal.

box, especially in day 2. In general, the output temperature of the unit (output of the heating coil) present a averaged NRMSE lower than 12% which can be interpreted as a maximum averaged deviation of 1.2°C when the range of the output values is 10°C.

Table 3. NRMSE for the output temperature for each component.

NRMSE [%]	Mixing box	Cooling coil	Heating coil
Day 1	9.49	6.64	9.18
Day 2	17.73	10.38	12.75
Day 3	13.36	11.46	12.93
Day 4	8.11	8.39	13.37
Day 5	7.58	7.67	10.67
Mean	11.25	8.91	11.78

CONCLUSION

An automated calibration methodology for the three most common heat exchangers in an air handling unit was presented. A case study using real operation data and Modelica based steady-state models was discussed showing the potential application of this methodology. This methodology can be applied for other active components found in a typical air handling unit – e.g. a humidifier -, provided the two part separation (heat/mass exchanger and mechanical control element) can be done. These calibrated models are deemed suitable for real-time applications of controls and fault detection and diagnosis as well as hardware in the loop simulations given the automation of the calibration methodology and the overall low computational requirements for simulation.

Using the proposed methodology it is possible to keep simulation errors within limits accepted for real applications.

Plots of the resulting hysteresis curve can directly be used for fault detection and diagnosis. In particular, with a simple look at the curves generated in this work, the presence of a stuck or mechanical wear could be detected. The same observation can be done for other typical faults (e.g. passing valves). This detection could be automated by using a simple classifier, for example a semi-supervised learning algorithm. In addition, if the proposed calibration process was implemented in real-time (with periodic retraining), the tool could be used as a supporting FDD system.

FUTURE WORK

Next step in this research is to include the possibility of making an initial fault detection and diagnosis using the information obtained from the calibration.

In addition, a graphical user interface will be developed in order to integrate Modelica and Python code and provide an easy-to-use tool.

NOMENCLATURE

Models

eff	effectiveness	[1]
Q	heat transfer	[W]
c	specific heat capacity	[J/kg·K]
C	capacity flow	[W/K]
n	saturation efficiency	[1]
mflow	mass flow rate	[kg/s]
T	temperature	[°C]
Twb	wet bulb temperature	[°C]
W	humidity ratio	[1]
Wsat	humidity ratio at saturation	[1]

Optimal control signal

μ	Preisach model coefficients
U	optimal value
$\boldsymbol{U}^*$	optimal control signal
Y	output of the plant (simulated output)
R	reference (measured output)
$\boldsymbol{O}$	control signal from BMS
ε	error tolerance

Subscripts

a	air
I	input
O	output
w	water
s	steam
MB	mixing box
CC	cooling coil
HC	heating coil

Functions

$\max(\cdot, \cdot)$	largest value between arguments
$\min(\cdot, \cdot)$	smallest value between arguments
$R_{\alpha,\beta}$	relay hysteron

REFERENCES

ASHRAE, 2002. *ASHRAE Guideline 14. Measurement of Energy and Demand Savings*,

ASHRAE, 2009. *ASHRAE Handbook: Fundamentals (SI edition)*, Atlanta, GA: American Society of Heating, Refrigerating and Air-conditioning Engineers.

European Parlanment and Council of the European, 2010. DIRECTIVE 2010/31/EU OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 19 May 2010 on the energy performance of buildings (recast). , pp.13–35.

Febres, J. et al., 2013. HEAT VENTILATION AND AIR CONDITIONING MODELLING FOR MODEL BASED FAULT DETECTION AND DIAGNOSIS. In *13th International Conference* *of the International Building Performance Simulation Association*. Chambéry - France.

Febres, J., Sterling, R. & Keane, M., 2014. A Python-Modelica Interface for Co-Simulation. In *International Conference on Sustainability and Energy in Buildings*. Cardiff.

Kim, M. et al., 2008. Design of a steady-state detector for fault detection and diagnosis of a residential air conditioner. *International Journal of Refrigeration*, 31(5), pp.790–799. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0140700707002186 [Accessed December 11, 2014].

Lawson, C.L. & Hanson, R.J., 1995. *Solving least squares problems*, Society of Industrial and Applied Mathematics. Available at: http://epubs.siam.org/doi/book/10.1137/1.9781611971217.

Lemort, V., 2008. Development of Simple Cooling Coil Models for Simulation of HVAC Systems.

Orr, M., 1996. Introduction to Radial Basis Function Networks. In pp. 1–67.

Tan, X., Venkataraman, R. & Krishnaprasad, P.S., 2001. Control of hysteresis: theory and experimental results. In V. S. Rao, ed. *SPIE's 8th Annual International Symposium on Smart Structures and Materials*. pp. 101–112. Available at: http://proceedings.spiedigitallibrary.org/proceeding.aspx?articleid=907277.

Tashtoush, B., Molhim, M. & Al-Rousan, M., 2005. Dynamic model of an HVAC system for control analysis. *Energy*, 30(10), pp.1729–1745. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0360544204004761 [Accessed May 11, 2012].

Table 4. Model parameters and physical quantities

MODEL PARAMETER	COOLING COIL	HEATING COIL
Nominal air input temperature [°C]	25.0	6.3
Nominal air input relative humidity [%]	50.0	-
Nominal air output temperature [°C]	13.8	18.8
Nominal air output relative humidity [%]	88.0	-
Nominal air mass flow rate [m^3/s]	1.35	1.35
Nominal water input temperature [°C]	6.0	82
Nominal water output temperature [°C]	12.0	71
Nominal water mass flow rate [kg/s]	0.97	0.47
PHYSICAL QUANTITY		
Air specific heat capacity [J/(kg·K)]	1006	
Water specific heat capacity [J/(kg·K)]	4186	
Atmospheric pressure [Pa]	101325	